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ABSTRACT

In this article we revive, extend and improve the approach used in a series of influential papers written in the 2000s to estimate how changes in the supply of immigrant workers affected natives' wages in the US. We begin by extending the analysis to include the more recent years 2000-2022. Additionally, we introduce three important improvements. First, we introduce an IV that uses a new skill-based shift-share for immigrants and the demographic evolution for natives, which we show passes validity tests and has reasonably strong power. Second, we provide estimates of the impact of immigration on the employment-population ratio of natives to test for crowding out at the national level. Third, we analyze occupational upgrading of natives in response to immigrants. Using these estimates, we calculate that immigration, thanks to native-immigrant complementarity and college skill content of immigrants, had a positive and significant effect between +1.7 to +2.6\% on wages of less educated native workers, over the period 2000-2019 and no significant wage effect on college educated natives. We also calculate a positive employment rate effect for most native workers. Even simulations for the most recent 2019-2022 period suggest small positive effects on wages of non-college natives and no significant crowding out effects on employment.

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Introduction and Review of the Literature

A classic question in the economics literature, and still at the center of the political debate as the US labor force is shrinking but federal immigration reforms are unpopular amid increasingly anti-immigrant sentiment, is: *what is the impact of immigrants on wages and employment of US workers?* A series of influential papers, Ottaviano and Peri (2012) and Manacorda, Manning, and Wadsworth (2012) – which extended and complemented their predecessor paper, Borjas (2003) – developed and estimated a robust model to calculate the effects of immigrants on national wages of US (or UK) workers with different levels of education and age between 1960-2000.

These studies considered immigration as a change to the national supply of a set of labor market skills and examined the effect on natives' wages in the long run, accounting for competition and complementarity with the newly arrived workers. Based on a nested constant elasticity of substitution (CES) production function with skill cells as labor inputs, their framework is a reasonable approximation of US labor markets in the long run, when workers' wages equate their marginal productivity and competition depends on skill types. These influential papers have been cited extensively and have provided benchmark calculations to assess the effects of immigrants on US wages in the 1980s and 1990s.

However, while influential, their approach has not been revived to estimate the impact of more recent immigrant flows (post-2000), or expanded to use current econometric techniques for estimating the key parameter values (the original studies use Least Squares estimation with panel data). Nor have they been used to analyze the long-run effects on native employment (which was assumed as not responding to immigration) or to investigate potential channels for the imperfect labor market competition between natives and immigrants (especially the impact of immigrants on occupational specialization of natives).

This paper, building on the insights of those seminal studies, introduces a new more rigorous identification approach and extends the analysis to include the effects on native employment and occupational specialization outcomes, allowing us to provide a complete picture of the impact of immigration on US native labor market outcomes nationally. Additionally, we update the analysis to the deeply changed trends in immigration to the US in the 2000-2022 period, as compared to the 1980-2000. Since 2000, immigration flows have become smaller and more concentrated among highly educated individuals, with a negative net change of immigrants with low levels of education (less than high school degree) over the last two decades. This change, on its own, warrants revisiting those findings and could change the predicted implications on native labor market outcomes.

Before discussing our innovations, it is useful to review the three approaches most commonly used in papers estimating the effects of immigrant on labor market outcomes in order to frame, within them, this contribution.[1]

A first line of research, which stresses credible causal identification through the use of "natural experiments", has focused on identifying exogenous, sudden and significant changes in immigrant supply specific to one (or few) individual location(s) in the US. This approach compares the response of local natives' wages, employment and other labor market outcomes in the location(s) where the sudden immigration occurred ("treated" area) to locations where it did not ("control" areas). Famous studies using this approach include a seminal paper by Card (1990) studying a large inflow of Cubans to Miami in 1981, the so-called *Mariel Boatlift*, as well as a series of subsequent papers that revisited this event (Borjas (2017), Peri and Yasenov (2019) and Clemens and Hunt (2019)). Other examples include Peri, Rury, and Wiltshire (2020), which used the inflow of Puerto Ricans to Orlando after Hurricane Maria, and Kugler and Yuksel (2011), which used the inflow of Central Americans after Hurricane Mitch.[2] While this approach may bring us closer to causally identifying the average impact of a sudden immigration event, the specific nature of the immigrant groups involved, of the timing, and location make results potentially not generalizable or externally valid. Even more crucially, it is challenging to translate these estimates to national effects that stem from larger, slower and more predictable immigration flows, usually with different distribution across skills (which is what we need to inform immigration policy).

In a second approach, which better addresses this external validity concern, economists have exploited changes in the inflows of immigrants *across all US commuting zones* (which approximate local labor markets) driven by increases and decreases in immigration flows from specific countries of origin. These flows are then distributed as differential "shocks" across US locations as preexisting networks of immigrants are known to affect the location choices of new arrivals. Several papers have used this variation in building "shift-share" instruments to compare labor market outcomes across US commuting zones (Card (2001, 2009); Peri and Sparber (2009); Peri, Shih, and Sparber (2015); Monras (2020)). After verifying the shift-share IV is not correlated with preexisting labor market trends, this approach can be used to analyze the local impact of immigrants.

The shift-share approach has evolved and been improved based on key criticisms. Recent developments provide stringent tests for identification validity which have increased the credibility of local area IV approaches (Goldsmith-Pinkham, Sorkin, and Swift (2020)). At the same time, papers using this approach have considered departures from the classical labor market approach. Some have introduced imperfect competition in the labor market and

[1] There were important studies in the recent years summarizing the effect of immigrants on labor market outcomes in the US. Chapter 5 of National Academies of Sciences and Medicine (2017) is probably the most well-known and covers a large body of research.

[2] Application of this approach to other countries' immigration episodes are numerous and some of them are summarized in Tumen (2015).

monopsony power of firms at the local level in models that produce negative wage effects of immigration (and positive effects on firms profit) as new flows of immigrants increase the bargaining power of the firms (Amior and Manning (2020); Amior (2020)). Other studies have examined how certain institutions, such as the minimum wage (Edo and Rapoport (2019)), interact with the inflow of immigrants to attenuate wage effects (at the same time exacerbating employment effects) at the local level.[3]

While interesting and useful, the local area literature, and the focus on monopsony power of firms has limitations. In particular, they may be only partially useful in thinking of the recent (post-2000) immigration to the US. First, as the analysis is local, one needs to analyze incumbents' geographic mobility in response to immigration and capture the "spillover effects", not just the local effect, to obtain national labor market results. The internal mobility response of natives and of immigrants can be large, as studies suggest (Borjas (2001); Basso and Peri (2020); Dustmann et al. (2017)), and inferring effects on national markets from local ones is not easy, requiring modelling and assumptions (Amior (2020)).

Second, by focusing on the impact of immigrants across geographies, this literature has somewhat oversimplified the analysis of skill-composition, often considering immigrants and natives as one type of undifferentiated labor (e.g., Amior and Manning (2020); Amior (2020)). This simplification limits this literature's ability to differentially study effects of immigration by skill groups.

Third, and most importantly, the focus on monopsony effects or the role of minimum wage present immigration as an inflow of less educated and often of undocumented immigrants, which is closer to US immigration in the 1990s.[4] However, it does not accurately reflect immigration post-2000, in which the net flow of immigrants with no high school degree was negative, the number of undocumented immigrants did not grow, and college educated immigrants expanded to becoming the largest group in the country.

Complementing these two lines of inquiry, but focusing on skills and on US national labor markets, we revive a third approach pioneered by Borjas (2003), Ottaviano and Peri (2012) and Manacorda et al. (2012). We refer to this as the national "factor-supply" approach which analyzes the national effects (i.e., for the whole US) of immigration on wages of native workers aggregated in different skill groups.

Three features of this approach are worth discussing. First, it separates the US national labor market into national markets (cells) by skills (education and experience) and allows

[3] Additionally, the recent literature (mostly outside of the US) has taken advantage of individual longitudinal data to follow the impact of immigration on native individual outcomes, rather than on aggregate labor market outcomes for natives (Foged and Peri (2016); Dustmann, Schönberg, and Stuhler (2017)). While this is a very important evolution, the evaluation of aggregate effects on natives by skill group is still a central question.

[4] Monras (2020) is an interesting paper combining a cross-commuting zones shock with a structural model to identify the effect of low skilled immigration in the 1990s.

for stronger competition among workers with similar skills. Immigrants are considered an additional skill group in each skill-cell and their inflow represents a supply change specific to each type of skill. This approach, by innovatively considering skill cells and labor markets nationally over the long run (decade), internalizes geographical mobility responses.

Second, the approach uses a simple nested CES production function of different skill groups (worker types) plus capital and, by equalizing marginal product of workers to wages, derives wage equations. Using them, it estimates the key elasticity parameters between worker types. As highlighted by Ottaviano and Peri (2012), when applied to immigration this model allows one to compute the immigrant-native elasticity within each education-experience cell as a key parameter of interest, which is distinct from how the approach is used to estimate the education premium (e.g., Autor, Goldin, and Katz (2020)) or the age premium (Card and Lemieux (2001)). One limitation of these original studies is that once they controlled for skill-specific demand shifters using fixed effects, and trends in a panel regression, the estimates were simple applications of Least Square methods without a careful focus on identification.

Third, these studies used the estimated parameters and the CES-derived formulas to calculate the long-run wage effect of immigration for each native workers' group, assuming no employment response in a classical model with rigid supply of labor. This allowed the approach to predict national effects of immigration on natives' wages for each skill group, depending on the size of the inflow in each cell, and thus specific to the period considered.

Several policy papers adopted this approach (e.g., Greenstone and Looney (2010, 2014); Edwards and Ortega (2017)) to evaluate the wage effects of immigration or the effects of removing undocumented immigrants on natives' earnings. Additionally, the complementarity between immigrants and natives, found in Ottaviano and Peri (2012), spurred a subsequent literature considering whether natives' occupational/skill upgrading in response to immigration was a potential mechanism (Peri and Sparber (2009); Llull (2018); Hunt (2017)). None of these papers, however, were expanded, modernized or extended over time. The main finding, still broadly cited, of Ottaviano and Peri (2012) was that immigrants and natives in each skill-cell (i.e., labor market) are not perfect substitutes. Their degree of complementarity was strong enough to generate average positive effects of the 1990-2006 immigration on wages of most natives, with zero or small effects even for the group of least educated workers (i.e., individuals without high school diploma), in spite of the large inflow of immigrants in this group.

This paper revives, expands and improves upon the contributions of the national "factor-supply" approach in four substantial ways. First, we update the estimates of the key elasticity between immigrants and natives, extending the analysis to 2000-2019 and by employing a new Instrumental Variable (IV) estimation approach. We start by using the change in working-aged population for each group to capture labor supply shifts, then we implement a new skill-cell based shift-share approach to generate variation in immigrant labor supply across skills along with demographic-driven changes to generate changes in native labor supply across skills. We test the strength and validity of the IV and use this method to produce estimates of complementarity between natives and immigrants of similar skills.

Second, using the same framework and IV approach, we estimate the impact of immigrants on native employment-population ratio, a margin not yet considered by the "factor-supply" approach which often implicitly assumes rigid native labor supply. These results speak more directly to the potential "displacement" or "crowding out" effects of natives in each skill group at the national level. Third, we analyze occupational upgrades of natives in response to immigrants in each skill cell as mechanisms consistent with specialization, and which rationalize the complementarity and the positive employment effect from immigration.

Finally, using these updated estimates, we calculate the native wage (and employment) effect in response to the immigration flows of the 2000-2019, and estimate the potential impact of the more recent inflow of immigrants between 2019-2022.

We identify three main findings. First, using our more credible IV as supply shifts (for immigrants and natives) and more recent data, we estimate an elasticity of substitution between immigrants and natives post-2000 around 17-20 in our preferred specification which uses wages of pooled workers (male and female). If we allow the immigrant-native elasticity to differ by education group, we find an even smaller value in the post-2000 data for college educated (value around 10) and imperfect substitutability within each group. These estimates imply similar or even stronger complementarity between immigrants and natives than estimated in Ottaviano and Peri (2012).

Second, the 2SLS estimates of the effect of immigration in each skill cell on natives' employment-population ratio is positive, significant and between 0.05 and 0.095%, in response to a 1% increase in immigrant employment. This is consistent with rather rigid supply, a demand boost driven by immigrant-native complementarity as well as with occupational upgrading in response to the inflow of immigrants. We estimate that an average increase of native wage by 0.01 to 0.02% for each 1% growth of immigrant share can be fully due to shifts of natives into better-paying types of occupations in response to immigration.

Finally, using these elasticity estimates, we calculate that the recent 2000-2019 inflow of immigrants increased the wages of less educated natives (high school degree or less) by 1.7 to 2.6% and on average increased wages for natives by 0.5 to 0.8%, depending on parameter specifications, and had no significant wage effect on college educated natives. Additionally, in the 2000-2019 period, natives' employment rate increased on average by 2.4% in response to immigration. Focusing on the most recent years, the predicted effect of the immigrant inflow from 2019 to 2022 is small, but still positive, around a +0.9% wage effect for less educated natives and a +0.1% for average wages of natives.

An additional contribution of this paper is to revive the factor-supply conceptual approach to help both economists and policy-makers think about the effects of immigration on native wages and employment. We think that the CES framework in Ottaviano and Peri (2012), revived in this paper, is useful to discuss and illustrate the issues related to skill complementarity, the impact of immigration on skill cells productivity, and the difference in partial and total effects. From this perspective, the present paper brings that model to current US immigration data and uses the modern econometric techniques needed to produce more credible and useful estimates.

In addition, we consider the national "factory-supply" framework relevant to many classic topics in economics by providing a framework to think through labor market effects of education and technology using a CES production (namely Goldin and Katz (2009)) and the effect of demographic change on age premium (Card and Lemieux (2001)). Some of these classic papers have been updated to recent data and extended to the inclusion of additional elements (e.g. in Autor et al. (2020)). We do the same for the extended "factor-supply" model with the intention of updating and refining the econometric analysis to make this framework and available estimates useful for graduate Labor/Macro classes and policy analysis.

The rest of the paper proceeds as follows. Section 1 describes the data used and shows trends for recent inflow of immigrants to the US by education group; Section 2 presents the framework for our estimation of the wage equations and the key complementarity parameter between immigrants and natives; Section 3 both shows our Least Square estimates updating Ottaviano and Peri (2012)'s ones and includes preliminary estimates of the effect on national employment-to-population ratio of natives using an elementary IV; Section 4 describes the new and improved IV strategy for identification of the key parameters, shows the IV's robustness and validity, and presents the main 2SLS estimates; Section 5 shows the estimates of occupational upgrading of natives; Section 6 calculates the effects of immigrant inflows during the 2000-2019 and 2019-2022 periods on wages and employment of natives. Finally, Section 7 concludes the paper.

1 Data and recent trends in immigration

First we discuss our data sources and the definitions used for our most relevant variables, and then we describe recent trends in immigration and wages for US workers by skill groups.

1.1 Data, variables and sample description

We closely follow Ottaviano and Peri (2012) and Borjas (2003) to define and construct our variables and sample. We use employment and wage data from the integrated public use microdata samples (IPUMS), where the original sources are the US Decennial Census from 1960 to 2000 and the 1-in-100 samples for 2005-2010-2015-2019-2022 American Community Survey (Ruggles, Flood, Sobek, Backman, Chen, Cooper, Richards, Rogers, and Schouweiler (2023)).

We construct two slightly different samples to build employment measures and wage measures. In both samples, we consider people aged 18 and older in the Census year of interest not living in group quarters, who worked at least one week in the previous year. As our goal is to obtain a representative average wage for a given group of people with similar education and work experience, the wage sample is more restrictive: we drop individuals who either did not report a valid income or are self-employed. For each of the two samples, we also create a subset of full-time workers only, identified as those working at least 40 weeks in the year and at least 35 hours in the usual workweek. This allows us to construct full-time employment versions of our main measures.

Since our employment and wage measures of interest will be aggregated to the education-experience level, for each year in our data we build 32 cells identified by different combinations of education and experience, as in Ottaviano and Peri (2012). Specifically, we define four education groups using details on individuals' educational attainment: individuals with no high school degree, high school graduates, individuals with some college education, and college graduates (Bachelor's degree or more). Relying on the assumption that people enter the labor force at different ages depending on their education attainment, we define eight experience groups, grouping individuals into 5-year intervals of potential experience in the labor market: individuals with 0-5 years of experience, individuals with 5-10 years, and so on, with the eighth and final group characterized by 35-40 years of experience.[5,6]

We consider three main variables to measure labor supply. First, we build a measure of hours worked by cell by calculating the hours of labor supplied by each individual working a positive number of weeks during the previous year, multiply these by the individual weight (PERWT), and finally aggregate total hours within each education–experience cell. Alternatively, we calculate the cell-specific employment level (i.e., count of employed people), summing up the person weights for all individuals in the cell who worked a positive

[5] As in Ottaviano and Peri (2012), we assume that people without a high school degree enter the labor force at age 17, those with a high school degree enter at 19, those with some college enter at 21, and those with a college degree enter at 23.

[6] Individuals with 0 years of potential experience and with more than 40 years of potential experience are dropped from our sample.

amount of weeks during the previous year. Finally, we compute the population in each cell by summing the person weights of the people belonging to each cell (PERWT) regardless of their working status. We use population in the cell as a more "exogenous" measure of labor supply for a given skill group as well as to calculate employment/population ratios.

As for wage measures, in line with Ottaviano and Peri (2012), we construct the cell-specific average weekly wage by calculating the weighted average of individuals' real weekly wages (equal to annual wage and salary income, INCWAGE, converted to 1999 US dollars using the CPI multiplier provided by IPUMS, adjusted for top-coding, and then divided by weeks worked in a year), where weights are the hours worked by the individual times their person weight. For each cell, we compute not only the overall employment and wage measures aggregating all individuals, but also gender-by-origin specific measures by separating individuals in the cell into four groups: native males, native females, foreign-born males and foreign-born females. The status of foreign-born is given to those individuals who are noncitizens or are naturalized citizens. Clearly, differentiating by nativity will be crucial for our analysis.

Finally, in our analysis on occupational upgrading in Section 5, we define a measure of natives' occupational quality for each education-experience cell as follows. We apply our previously described sample restrictions to the 1980 US Decennial Census, the first period of our sample of analysis, to compute the average wage by occupation. We do so by averaging individual weekly wages, computed by diving the annual wage and salary income (INCWAGE) by weeks worked, and weighting each wage by the individual weight (PERWT). We identify occupations by relying on a version of the 1990 Census Bureau occupational classification scheme that provides researchers with a consistent classification of occupations over time (OCC1990). Since each occupation breaks out into more specific occupations, or is combined with others into a more general occupation, over the decades, we pick a classification from 1990 which is the midpoint of our initial sample (from 1960 to 2019), limiting crosswalks and adjustments. The new variable, 1980 average wage by occupation, is then assigned to each individual in the Decennial Census and ACS data of interest based on their reported occupation in that period. Similarly to the wage and employment measures, this variable is aggregated within education-experience groups, using individual weights of workers in each cell. We compute this measure only for natives, and separately for full-time workers and for men and women.

1.2 Immigration and wage trends

Figure 1 shows the evolution of the foreign-born adult population resident in the US between 1960 and 2022. The data are from the Decennial Censuses between 1960 and 2000 and then from the American Community Survey 2005, 2010, 2015, 2019 and 2022. These dates and sources are what we use throughout the paper. The four lines in the figure capture the populations of foreign-born individuals 18 years and older with no high school degree (red solid line), high school degree (red dashed line), some college education (dashed blue line) and college degree or more (solid blue line) over time.

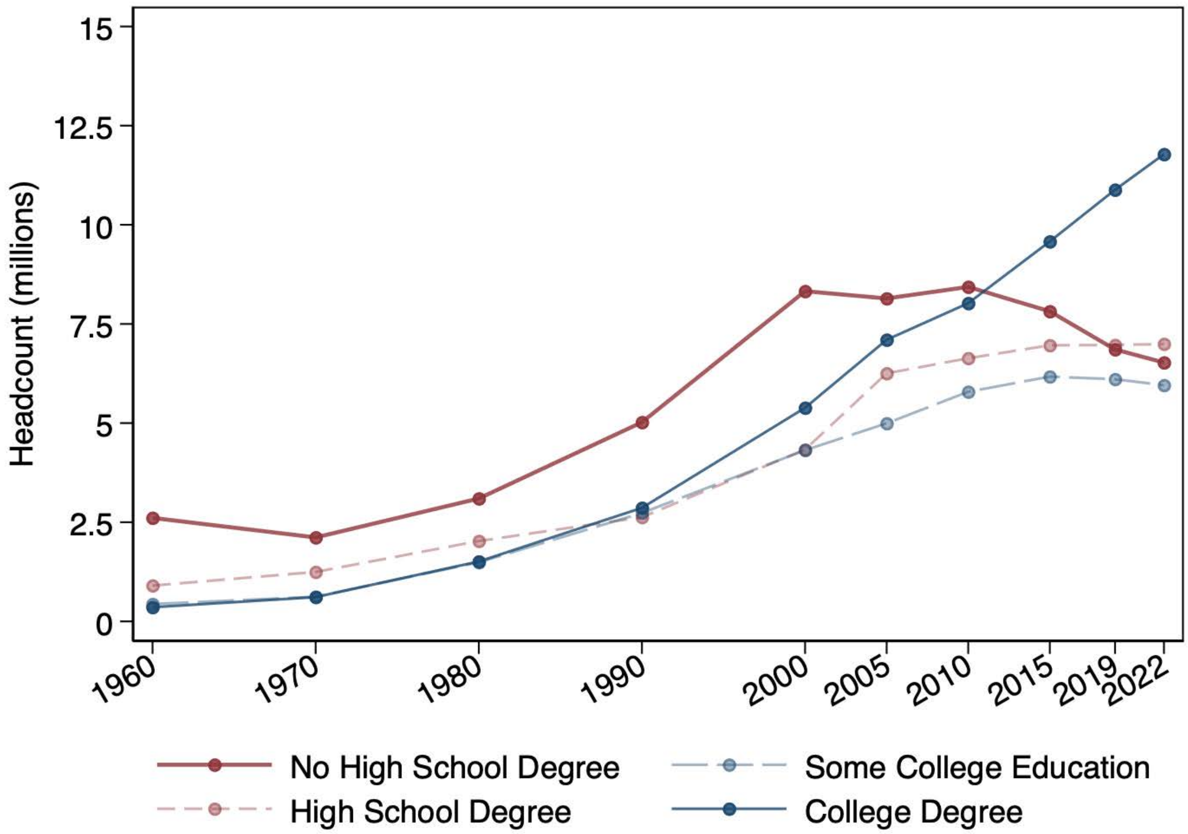
The graph highlights the stark trend differences before compared to after 2000. Between 1970 and 2000 all groups grew in numbers and at comparable rates. In particular immigrants groups with no high school degree was the largest and growing at the same pace as the other groups. However, after 2000, lower educated immigrants stopped growing and actually declined in size (implying negative net migration), particularly after 2010. The population of the two intermediate education groups (those with high school diploma and those with some college education) slowed their growth and stabilized in size. In contrast, the number of college educated immigrants both continued to grow and possibly accelerate; since 2015, college educated immigrants are the largest group of foreign-born in the US adult population. The graph suggests that net immigration to the US went from large and unskilled intensive in the 1980-2000 period to smaller and skill-intensive in the 2000-2022 period.

Figure 2 further explores this change in composition by depicting the trend growth for each education group as a proportion of their initial population, standardized to one, and separating the sub-periods 1980-2000 (left panel), 2000-2019 (middle panel) and 2019-2022 (right panel). In the left panel of the figure, which represents the changes in the 1980-2000 period, we see that all education groups at least doubled their 1980 size by 2000. As a proportion of its initial size, the group of immigrant college graduates grew by a factor larger than 3. The group with no high school degree also grew by a remarkable 2.6 times, and the two intermediate groups more than doubled in size.

This period experienced the fastest immigrant population growth in the last 60 years. The 2000-2019 period, in contrast, shows a very different picture. First, the overall growth of each group is much smaller. Second, while college graduates still exhibit the highest growth rate, with population increasing by a factor of 2 by 2019, the two intermediate education groups grew at a much slower rate, increasing by around 50% their size in 20 years, and the group of individuals with no high school degree experienced a significant decline (about -10%). Finally, the much shorter post-Covid-19 period for which we have reliable census data, 2019-2022 period, which combines a drop in immigration during the pandemic and a subsequent immigration surge, confirms the dynamics of much smaller and more college-intensive immigration flows.

In Figure 3 we translate these population changes more directly into changes in labor supply available to the US economy. Specifically, we represent the percentage change in

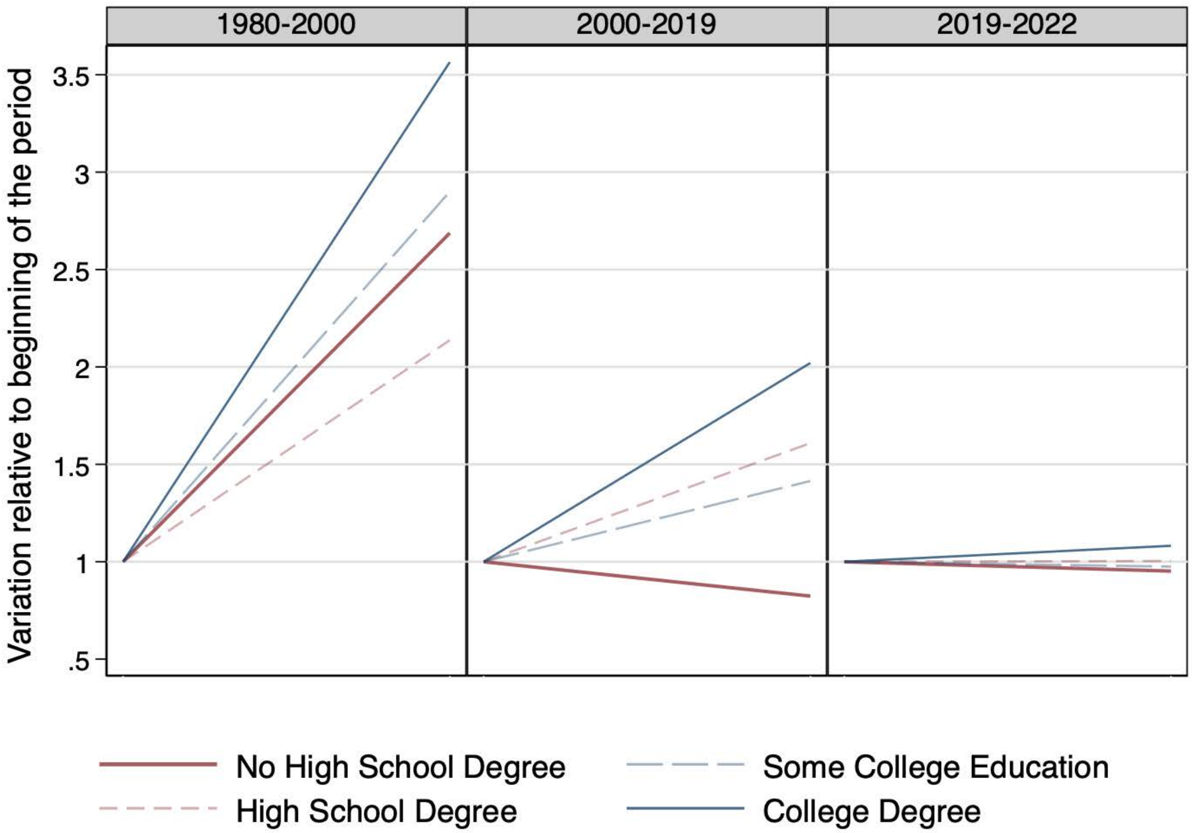
Figure 1: Evolution of immigrant population by education group (1960-2022)



Notes: This figure depicts the evolution of foreign-born population in the US by education group. The ten dates used for this figure correspond to those used throughout our analysis (1960, 1970, 1980, 1990, 2000, 2005, 2010, 2015, 2019, and 2022). We restrict the sample to foreign-born individuals aged 18 years and older.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

hours worked due to net immigration in each group (by education) and in three sub-periods (1980-2000, 2000-2019, 2019-2022) in the left panel. Then for comparison, we show the percentage change in weekly wages of native US workers for the same education groups and sub-periods (right panel), to examine correlations across periods and/or education group. The left panel clearly depicts the U-shaped pattern of change in supply of skills due to immigrants in the 1980-2000, as identified in Ottaviano and Peri (2012). During the 1980s and 1990s, the growth in labor due to immigrants was much larger (20% increase) for the most and least educated groups (no high school degree and college graduates) than for intermediate groups (high school degree and some college). This pattern, however, changed significantly in the 2000-2019 and 2019-2022 periods. First, the growth in each group's hours worked due to net immigration is much smaller. Second, the group of college graduates experienced the largest increase (+13% in 2000-2019 and +1.5% in 2019-2022) while

Figure 2: Period-specific factors of growth of immigrant population by education group



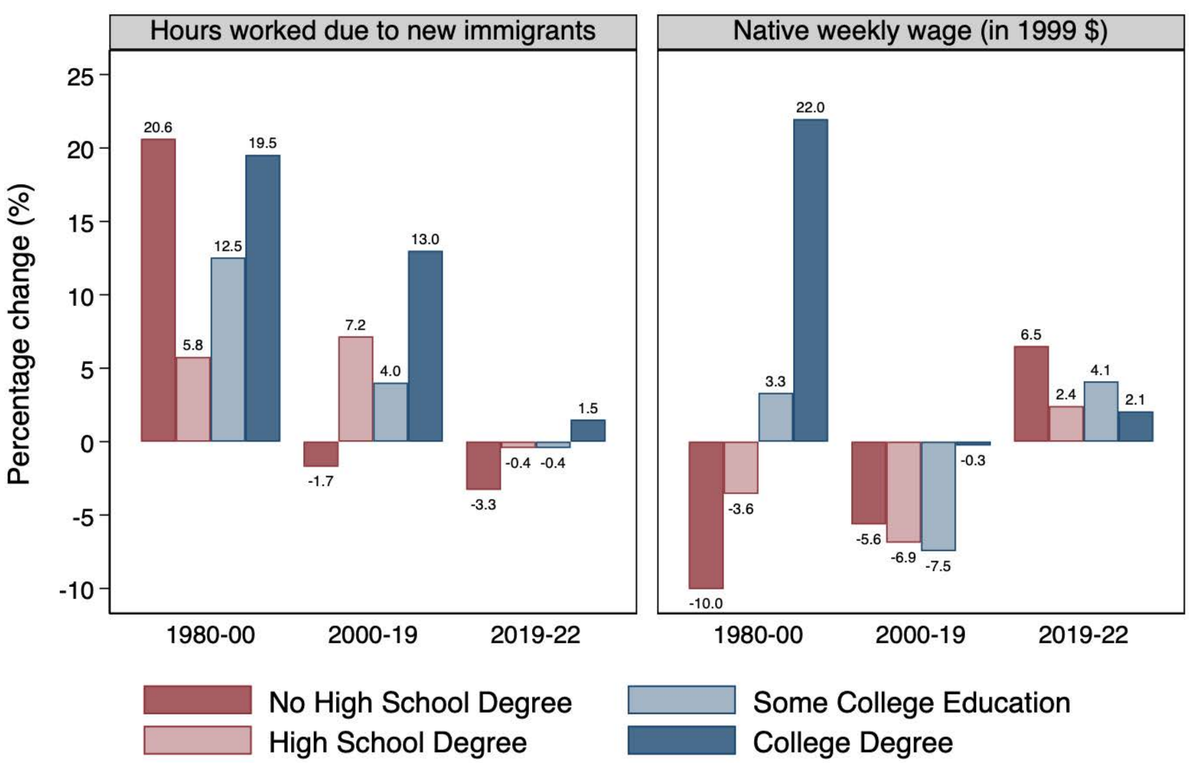
Notes: This figure reports factors of growth of the foreign-born population by education group and specific for the three sub-periods of interest (1980-2000, 2000-2019, 2019-2022). For this figure, we only use data for the beginning and the end of each sub-period, without intermediate data points. For each education group, we set population equal to 1 at the beginning of each sub-period (1980, 2000 or 2019) and then we compute the ratio between the initial population and the final population of the group at the end of the sub-period of interest (2000, 2019 or 2022, respectively) to obtain the factor of growth. We only include foreign-born individuals aged 18 years and older.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

the group with no high school degree the smallest (negative) change in hours worked due to immigrants (-1.7% in 2000-2019 and -3.3% in 2019-2022). Net immigration in the post-2000 years can be characterized as shrinking the supply of the least educated workers and significantly increasing the supply of college educated ones.

For reference, the right panel of Figure 3 shows the percentage changes of native weekly wages for the same periods and education groups. In the 1980-2000 period, when immigration changed the supply of labor in the described U-shape, the changes in native wages show a monotonic increase in dispersion with college-educated wages growing very fast and wages of those with no degree declining fast. The following periods, 2000-2019 and 2019-2022, exhibit a smaller disparity between wage growth at the top and at the bottom of the schooling range, with average wages declining in 2000-2019 and increasing in 2019-2022. Notably, in no period across any education group is there a clear negative association between immigrant-driven labor supply growth and changes in native wages. This negative correlation is what a canonical model with 4 skill groups and perfect substitution of immigrants and natives within a group would predict.

Finally, Appendix Table 11 shows more systematically changes in the share of immigrants and in real wages across education-experience groups between 2000 and 2019. As it was also the case in Ottaviano and Peri (2012) for the 1990-2006 period, there is no clear negative correlation between column (3) and column (4) of Table 11, revealing no "prima facie" evidence of pure wage-competition effects from an increase in labor supply in each skill group due to immigration.

Figure 3: Percentage changes in hours worked and native wages by education group



Notes: This figure presents percentage changes in hours worked that are due to net immigration (left panel) and percentage changes in real weekly wages of native workers (right panel) by education group. Changes for the period 2000-2019, which are also reported in Appendix Table 11, are compared here with their corresponding values in two other periods, 1980-2000 and 2019-2022.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

2 Framework and estimating equations

2.1 Nested CES production function

The framework we use follows the seminal papers by Borjas (2003) and Ottaviano and Peri (2012). We assess the long-run effect of immigration on native wages using an aggregate production function that combines physical capital (K), a labor composite (L) and total factor productivity, TFP (denoted as A). Such a production function for the aggregate US in year t is represented as follows:

$$Y = A_t L_t^{\alpha} K_t^{1-\alpha} \tag{1}$$

where α is the income share of labor. An aggregate production function like (1) is routinely used in many macro and growth models to represent long-run production (such as in those presented in Chapter 1, 2 and 3 of Romer (2019)). The key modelling assumption to analyze the interplay between supply of different types of workers and their marginal productivity, which in the long run is equated to wage compensation, is that labor L_t is a nested CES composite of several different skill groups. Immigration changes the supply of different types of workers (skill cells) and this affects skill-specific marginal productivity, which in the long run equals wages, by changing relative scarcity of skills. The magnitude of the effects depends on the own and cross elasticity of substitution across skill groups and the relative change of each supply. By using this approach we stay close to the canonical model, and consider competitive labor markets in the long run. One important limitation of this approach is that we omit potential effects of immigration on productivity in the analysis, which could be an important consequence, especially in presence of high skilled immigration (see Peri et al. (2015)).

We acknowledge that physical capital is complementary to aggregate labor, and that it adjusts in the long run to keep the capital-labor ratio at the efficient level (by equating marginal productivity of capital to the long-run discount rate), which is proportional to total factor productivity. By applying this equilibrium condition for capital, one can rewrite the capital term from the production so that total output is a linear function of the labor composite, multiplied by a modified TFP term. Hence, aggregate productivity growth and the related accumulation of physical capital are responsible for the average wage growth in the long run. However, relative wages across skill groups depend on relative skill abundance and the skill group substitutability. In this case, immigration has an impact on long-run wages.

The labor aggregate L is first composed of a CES aggregation of workers with high (H) and low (L) levels of schooling as follows:

$$L_t = \left[\theta_{Ht} L_{Ht}^{\frac{\sigma_{HL}-1}{\sigma_{HL}}} + \theta_{Lt} L_{Lt}^{\frac{\sigma_{HL}-1}{\sigma_{HL}}}\right]^{\frac{\sigma_{HL}}{\sigma_{HL}-1}} \tag{2}$$

where θ_{Ht} and θ_{Lt} are the relative productivity of more and less educated workers and σ_{HL} is their elasticity of substitution. Following Goldin and Katz (2009) and Autor et al. (2020), we identify group H as workers with some college education or more, and group L as workers with high school diploma or less. This is an important partition in this framework which reflects very different performances of these workers in the labor market. Over the last three to four decades possessing college education has been a critical to access jobs and occupations with more intensive cognitive and analytical content, whose demand/productivity has increased substantially during this period (Autor and Katz (1999); Autor, Katz, and Kearney (2006, 2008); Autor (2010)). Within group L of workers with high school diplomas or less, and within group H of workers with college education or more, we then allow – as Ottaviano and Peri (2012) did – workers to be different from each other, in an additional layer of the CES nesting, as follows:

$$L_{Ht} = \left[\theta_{SCOt} L_{SCOt}^{\frac{\sigma_{HH}-1}{\sigma_{HH}}} + \theta_{CODt} L_{CODt}^{\frac{\sigma_{HH}-1}{\sigma_{HH}}}\right]^{\frac{\sigma_{HH}}{\sigma_{HH}-1}} \tag{3}$$

$$L_{Lt} = \left[\theta_{NDt} L_{NDt}^{\frac{\sigma_{LL}-1}{\sigma_{LL}}} + \theta_{HSDt} L_{HSDt}^{\frac{\sigma_{LL}-1}{\sigma_{LL}}}\right]^{\frac{\sigma_{LL}}{\sigma_{LL}-1}} \tag{4}$$

The parameters θ and σ represent the productivity of, and the elasticity of substitution between, these education sub-groups, respectively.[7]

Following Card and Lemieux (2001), Welch (1979), and several other papers that have analyzed the evolution of experience premium of workers, we allow for an additional CES nest, combining workers with different work experience (based on age) in each education sub-group k as follows:

$$L_{kt} = \left[\sum_{j=1}^{8} \theta_{kj} L_{kjt}^{\frac{\sigma_{EXP}-1}{\sigma_{EXP}}}\right]^{\frac{\sigma_{EXP}}{\sigma_{EXP}-1}} \tag{5}$$

where the 8 groups represent bins of 5 years, from 0 to 40 years of potential experience, beginning at the time of finishing schooling, and therefore varying for each education group. Finally, as in Ottaviano and Peri (2012) and Manacorda et al. (2012), in each education k-experience j group, natives (domestic workers, denoted by D) and immigrants (foreign-born

[7] In equation (3) for group H of workers, SCO and COD denote "some college education" and "college degree", respectively. In equation (4) for group L, ND and HSD stand for "no high school diploma" and "high school diploma".

workers, denoted by F) provide different skills (due to language, culture and schooling-type differences) that are combined in a final nest of the CES, with relative productivity equal to θ_{Dkj} and θ_{Fkj}, and elasticity of substitution equal to σ_{IMMI}, as follows:

$$L_{kjt} = \left[\theta_{Dkj} L_{Dkjt}^{\frac{\sigma_{IMMI}-1}{\sigma_{IMMI}}} + \theta_{Fkj} L_{Fkjt}^{\frac{\sigma_{IMMI}-1}{\sigma_{IMMI}}} \right]^{\frac{\sigma_{IMMI}}{\sigma_{IMMI}-1}} \tag{6}$$

We choose this CES approach and nesting structure for three reasons. First, this framework is consistent with the structure of several papers analyzing the effect of technological and schooling changes on wages (e.g., Goldin and Katz (2009)) and the effect of aging and demographic change on experience premium (Card and Lemieux (2001)). Second, it enables us to derive simple equations relating (log) wages to the (log of) employment for each skill group of workers to represent labor demand. These equations allow us to estimate the elasticity of substitution between skill groups, provided we identify genuine shifts of the supply across skill groups. Third, once we obtain the elasticity estimates across skills, this model allows us to evaluate/predict the impact of different historical immigration episodes or potential immigration scenarios on long-run wages of native workers in each skill group. The calculated effects work through changes in relative supply affecting marginal productivity of different groups of workers through complementary and competition.

2.2 Estimating wage equations and the elasticity of substitution

The production function described above, combined with the long-run equilibrium conditions that wages for each group of workers are equalized to their marginal productivity, implies a simple log-linear relation between wages and employment of each skill group. In particular, considering immigrant and native labor in each of the 32 education-experience cells, equating their wages to marginal product and taking the log-ratio of the two, implies the following equation:

$$\ln\left(\frac{w_{Dkjt}}{w_{Fkjt}}\right) = \ln\frac{\theta_{Dkjt}}{\theta_{Fkj}} + \frac{1}{\sigma_{IMMI}} \ln\left(\frac{L_{Fkjt}}{L_{Dkjt}}\right) \tag{7}$$

where $\left(\frac{w_{Dkjt}}{w_{Fkjt}}\right)$ is the average wage of natives relative to immigrants in education k-experience j group in year t , and $\left(\frac{L_{Fkjt}}{L_{Dkjt}}\right)$ is the employment of immigrants relative to natives. Equation (7) is the basis to estimate σ_{IMMI} – a crucial model parameter capturing the elasticity of substitution between immigrants and natives in the same education-experience labor market. The smaller this parameter is (larger complementarity), the more an inflow of immigrants will boost productivity and demand for native workers. Sometimes we will refer to $\frac{1}{\sigma_{IMMI}}$ as the intensity of complementarity between immigrants and natives. If $\frac{1}{\sigma_{IMMI}} > 0$, then native and immigrant workers are not purely competing (perfect substitutes) in a labor market, but have a degree of complementarity that increases as the estimate of this coefficient grows larger.

Assuming relative productivity of these two groups $\frac{\theta_{Dkjt}}{\theta_{Fkj}}$ can be captured by skill-specific fixed effects, year fixed effects and short-run fluctuations, and that the remaining variation of $\left(\frac{L_{Fkt}}{L_{Dkt}}\right)$ is driven by changes in the relative population of those two groups, uncorrelated with labor market conditions, then we can write equation (7) as follows:

$$\ln\left(\frac{w_{Dkjt}}{w_{Fkjt}}\right) = \phi_{kj} + \phi_t + \frac{1}{\sigma_N}\ln\left(\frac{Empl_{Fkjt}}{Empl_{Dkjt}}\right) + u_{kjt} \tag{8}$$

Under these assumptions, a panel Least Squares estimation of equation (8) generates a consistent estimate of the "intensity of complementarity" $\frac{1}{\sigma_{IMMI}}$. The term ϕ_{kj} captures a set of skill group fixed effects, the term ϕ_t represents time fixed effects, and u_{kjt} captures a random error that includes demand variation uncorrelated with supply changes and measurement error.

This is the econometric approach taken by Borjas (2003), Ottaviano and Peri (2012) and Manacorda et al. (2012). Here, we extend those results in terms of period, sample and specifications to assess how robust those estimates were. Then we innovate by introducing a new Instrumental Variable (IV) method that captures changes in relative supply more likely to be uncorrelated to relative productivity, thus reducing potential omitted variable bias. The estimated parameter, $\frac{1}{\sigma_{IMMI}}$, is directly related to the boost that relative native wages receive when the relative supply of immigrants increases. Larger values of this parameter will produce larger positive wage impacts of immigration on natives.

Once $\frac{1}{\sigma_{IMMI}}$ is estimated, one can construct the labor aggregate in equation (6), and use a similar log wage equation for each cell as function of the corresponding log labor composite in (6) to estimate $\frac{1}{\sigma_{EXP}}$, the complementarity across experience groups. Subsequently, by aggregating within education groups, and then within the college (H) and non-college (L) groups, one can calculate the elasticity of substitution σ_{HH}, σ_{LL} and σ_{HL}. Those parameters are not specific to the immigration literature, and have been estimated by several papers without relying on changes of labor supply driven by immigration. In particular, analyzing change in schooling, the education premium and the evolution of wage inequality, Katz and Murphy (1992), Goldin and Katz (2009), and more recently Autor et al. (2020), have estimated the parameters σ_{HH}, σ_{LL} and σ_{HL}. Similarly, using changes in natives' demographics, Card and Lemieux (2001) (as well as Ottaviano and Peri (2012)) estimated the experience and age premium, σ_{EXP}. Therefore, in calculating the total effects of immigration in Section 6, we will use a range of these parameters' estimates from the existing literature and will combine them with the newly estimated elasticity between immigrants and natives to obtain the total effects of immigration on wage of each skill group of natives.

Instead, in this article, we push further the implementation of a regression-like equation (8) to estimate not just the wage response but also the employment response of natives to immigration. In particular, we analyze how a percentage change in immigrant employment in each education-experience cell, $\ln\left(Empl_{Fkjt}\right)$, has affected the employment-population ratio of natives, $\frac{Empl_{Dkjt}}{Pop_{Dkjt}}$, in the same education-experience cell by estimating the following equation:

$$\frac{Empl_{Dkjt}}{Pop_{Dkjt}} = \phi_{kj} + \phi_t + \beta_{emp} \ln\left(Empl_{Fkjt}\right) + e_{kjt} \tag{9}$$

While the coefficient $\frac{1}{\sigma_{IMMI}}$ captures the relative complementarity boost provided by the immigrant inflow on relative native wages, the coefficient β_{emp} captures a potential additional long-run effect of immigrants in crowding in (if positive) or crowding out (if negative) of similar-skilled natives.[8] Using natives' employment-population ratio as the outcome, we identify whether new immigrants attracted natives into the national labor market or, instead, if they pushed them out of employment. Given the similarity of equation (8) and (9), we will use similar methods and similar instrumental variables in our estimates, as to proxy for exogenous changes of the immigrant labor supply. Notice that the dependent variable in equation (9) is only relative to natives and captures their employment-population ratio, while the explanatory variable is only relative to immigrants, and captures their employment (in log).

3 Updated Least Square estimates

3.1 The native-immigrant elasticity of substitution

Table 1 shows the estimated parameter, $\frac{1}{\sigma_N}$, from equation (8) across different samples and specifications. Panel A uses decennial census data over the longer period 1960-2019, whereas Panel B uses quinquennial data in the more recent period 2000-2019. The specifications, samples and estimation methods used are very close to those in Panel A of Table 2 of Ottaviano and Peri (2012). Hence, the table can be considered an extension and update of those estimates considering a longer period (namely the period 1960-2019, in Panel A) or focusing on the more recent period only (2000-2019 in Panel B). In either case the coefficient captures the intensity of complementarity between natives and immigrants that is affected (or driven) by more recent immigration.

[8]This coefficient is related to the supply elasticity of natives as well as to the wage effect of immigrants.

Notice that, as the dependent variable in equation (8) is $\ln\left(\frac{w_{Dkjt}}{w_{Fkjt}}\right)$, the estimates show the positive value of:

$$\frac{1}{\sigma_N}$$

while in Ottaviano and Peri (2012) the estimates reported were relative to the same coefficient but with negative sign:

$$-\frac{1}{\sigma_N}$$

as the dependent variable was $\ln\left(\frac{w_{Fkjt}}{w_{Dkjt}}\right)$.

The specifications of rows (1)-(4) in Panel A and Panel B follow the same sample, variable definitions and estimation methods as the first four rows in Table 2, Panel A of Ottaviano and Peri (2012). In the top three rows of Table 1 the labor supply measures are total hours worked (in the cell). The dependent variable is the log average weekly wages for men (row 1) women (row 2) or both pooled (row 3). In the fourth row we use employment (count of people working) instead of hours worker in a cell as measure of labor supply, and the dependent variable is the log average weekly wages for men. In the fifth row (of Panel A and B) we go beyond Ottaviano and Peri (2012) by proxying labor supply in the cell with log relative population in the cell, and in the sixth row we use log relative population to instrument log relative hours worked in the cell. The dependent variable in both cases is the log average weekly wages for men.

Specifications in row 5 and 6 replace employment as an explanatory variable with a proxy for labor supply – the cell population. The total count of people in the cell (defined by their education and age) rather than employment, varies with demographics and immigration forces, and therefore is less correlated to non-observable cell-specific productivity shocks. As for the column specifications, they differ in terms of worker's samples and estimation method. Specifications (1) to (4) include all workers with a positive amount of weeks worked in the sample, while (5) to (8) include only full-year full-time workers, identified as those working at least 40 weeks in the year and at least 35 hours in the usual work-week. Individual columns then differ for the set of fixed effects included and for weighting. Specifications (1) and (5) weight each cell by its employment and include no fixed effects; columns (2) and (6) include 32 cell (education by experience) fixed effects and year fixed effects; columns (3) and (7) use no weights; columns (4) and (8) push the fixed effects to be as extensive as possible by including all two-way fixed effects (year-education, year-experience and experience-year) in a regression, which is sometimes referred to as "fully saturated." This represents a more demanding specification than any used in the original analysis by

Ottaviano and Peri (2012).

Table 1: New estimates of ($1/\sigma_{IMMI}$) following Ottaviano and Peri (2012), Extended periods

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	All workers				Full-time workers only			
				Panel A: 1960-2019				
Men, Hours	0.037***	0.048***	0.049***	0.034	0.042***	0.060***	0.061***	0.010
	(0.009)	(0.011)	(0.014)	(0.027)	(0.010)	(0.011)	(0.014)	(0.020)
Women, Hours	0.033***	0.074***	0.071***	0.085**	0.035***	0.076***	0.067***	0.046*
	(0.009)	(0.015)	(0.014)	(0.033)	(0.009)	(0.013)	(0.013)	(0.026)
Pooled, Hours	0.023**	0.044***	0.035**	0.058*	0.028***	0.057***	0.048***	0.023
	(0.010)	(0.013)	(0.015)	(0.031)	(0.010)	(0.012)	(0.014)	(0.020)
Men, Employment	0.039***	0.051***	0.051***	0.039	0.041***	0.060***	0.061***	0.011
	(0.009)	(0.011)	(0.014)	(0.025)	(0.010)	(0.011)	(0.014)	(0.020)
Men, Population	0.043***	0.044***	0.047***	0.045*	0.051***	0.057***	0.060***	0.019
	(0.010)	(0.011)	(0.016)	(0.026)	(0.010)	(0.011)	(0.016)	(0.014)
Men, Hours (IV)	0.040***	0.040***	0.042***	0.045**	0.047***	0.051***	0.053***	0.020*
	(0.008)	(0.009)	(0.012)	(0.020)	(0.009)	(0.008)	(0.012)	(0.012)
				Panel B: 2000-2019				
Men, Hours	0.027*	0.069***	0.063***	0.075*	0.035**	0.074***	0.066***	0.079*
	(0.015)	(0.017)	(0.016)	(0.044)	(0.015)	(0.018)	(0.017)	(0.045)
Women, Hours	0.042***	0.070***	0.051**	0.065	0.051***	0.079***	0.054**	0.076
	(0.012)	(0.025)	(0.025)	(0.050)	(0.012)	(0.025)	(0.025)	(0.050)
Pooled, Hours	0.033**	0.068***	0.061***	0.073*	0.041***	0.073***	0.063***	0.076*
	(0.014)	(0.018)	(0.014)	(0.041)	(0.014)	(0.020)	(0.014)	(0.042)
Men, Employment	0.029**	0.067***	0.064***	0.087*	0.034**	0.074***	0.066***	0.082*
	(0.014)	(0.018)	(0.017)	(0.047)	(0.015)	(0.018)	(0.017)	(0.044)
Men, Population	0.024	0.065***	0.065***	0.088*	0.033**	0.066***	0.065***	0.088*
	(0.016)	(0.018)	(0.017)	(0.046)	(0.016)	(0.019)	(0.018)	(0.046)
Men, Hours (IV)	0.022	0.065***	0.064***	0.085***	0.029**	0.067***	0.065***	0.083***
	(0.014)	(0.016)	(0.015)	(0.032)	(0.014)	(0.016)	(0.016)	(0.032)
Weights	Yes	Yes	No	Yes	Yes	Yes	No	Yes
Cell FE	No	Yes	Yes	-	No	Yes	Yes	-
Year FE	No	Yes	Yes	-	No	Yes	Yes	-
All two-way FE	No	No	No	Yes	No	No	No	Yes

Notes: Panel A considers the 1960-2019 period, using 7 data points (1960, 1970, 1980, 1990, 2000, 2010, 2019). Panel B considers the 2000-2019 period, using 5 data points (2000, 2005, 2010, 2015, 2019). Each coefficient of the table represents a different OLS regression, whose outcome is (log) relative weekly wage (for men, women or pooled, depending on the row). In both panels, all specifications use (log) relative hours worked as measure for labor supply (main regressor), except for rows (4) and (5), which employ (log) relative employment and (log) relative population, respectively. Row (6) instruments (log) relative hours worked with (log) relative population, and the 2SLS estimate is reported. Cell employment is used as weight for regressions in rows (1) to (4) in both panels, while cell population is used for those in rows (5) and (6). Cell FE include education and experience main-effect terms plus their interactions. All two-way FE include all main-effect and interaction terms from the combination of the three dimensions (education, experience, year). Robust standard errors are clustered at the cell level (education by experience).
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

Several clear results emerge from Table 1. First, focusing on the top four rows of Panel A, which most closely reproduces the estimates in Table 2 of Ottaviano and Peri (2012) and simply extends them to 2019, most of the coefficient estimates are significantly different from 0 and on average around 0.05, implying an elasticity of substitution between natives and immigrants of 20. This was the value preferred in Ottaviano and Peri (2012) and represents a small but significant degree of complementarity between natives and immigrants. These results show that the original estimates are robust to extending and updating the sample.

Focusing on columns (2) and (6), which represent reasonable specifications including cell and year fixed effects and employment weights, the first four rows show all significant values of the coefficients, close to 0.06. Then, looking at the last two rows of Panel A, which use population variations either as an explanatory variable or as IV to isolate supply side changes, we find that the estimates are essentially unchanged, between 0.04 and 0.06 and highly significant and very precise. Capturing the variation of the labor supply with changes in population only, the original results are fully confirmed and the precision of the estimates is still remarkable.

We then consider the estimates of Panel B, which uses the same specifications as Panel A, and data for the 2000-2019 period only – this period was not covered in the seminal studies (Borjas (2003), Ottaviano and Peri (2012) or Manacorda et al. (2012)). The panel analysis uses shorter time intervals (5-years) but otherwise the same specifications as Panel A. The results on the intensity of native-immigrant complementarity are fully confirmed and possibly strengthened.

Overall, the coefficients are somewhat larger, often in the range between 0.06 and 0.08. Similar to Panel A, even the most demanding specifications with all two-way fixed effects and using population as IV show highly statistically significant coefficients in the vicinity of 0.07, implying an elasticity of substitution between natives and immigrants around 14. The complementarity between immigrants and natives revealed by these estimates is persistent to the last two decades, and possibly increased relative to the estimates pre-2000. The estimated elasticity of substitution (σ_{IMMI}) is between 12.5 and 16.6 in most cases. One explanation for the increase in complementary between immigrants and natives is that the recent composition of immigrants (increasingly college intensive, as discussed in Section 1) may be especially complementary to natives. In fact, in Table 2, we suggest this is precisely the case.

Finally, it is worth emphasizing that the estimated complementarity between natives and immigrants is robust; samples measuring wages of both men, women, full-time workers and all workers exhibit a similar estimated parameter. Additionally, the inclusion of progressively more demanding fixed effects hardly changes the estimates, especially in Panel B. As we will see in the simulations of Section 6, the larger estimated value of this parameter implies a larger "complementarity boost" to native wages from the increased inflow of immigrants (especially those with college education). The current estimates suggest that this boost became stronger in the post-2000 period.

Table 2 expands the estimates of $\frac{1}{\sigma_{IMMI}}$ to allow for heterogeneity across education groups. Specifically, we show the estimates of $\frac{1}{\sigma_{IMMI}}$, when using the wage variable for the men sample and instrumenting relative hours with cell population, but also allowing separate coefficient estimates for each education group (no high school diploma, high school diploma, some college education, college degree or more). Estimates of the same specifications relative to women's and to pooled relative wages are reported in Appendix Table 12. As above, we consider the estimates for the whole period 1960-2019 in Panel A and limited to the more recent period 2000-2019 in Panel B. All specifications include experience fixed effects and separate the immigrant-native elasticity by education. Specifications (1) and (2) include all workers and (3) and (4) only full-time workers, while (1) and (3) use cell weights equal to the employment of the cell and (2) and (4) do not use weights.

Two features emerge from both panels. First, complementarity (i.e., a significantly positive value of the coefficient) is present for each education group, and it is stronger in the recent period, as the 2000-2019 estimates are 1.5 to 2 times as large as those for 1960-2019. Second, in most specifications, complementarity is stronger for individuals without a high school diploma and, even stronger (especially for full-time workers), for college graduates, namely the least and the most educated group of workers. In the post-2000 period, native-immigrant elasticity of substitution had a value as low as 9-10 for the two groups at the extremes of the education range, while it was as large as 40-50 for the intermediate ones. This is strongly consistent with existing evidence that immigrants are most different from natives in low-education job types, where they are employed in occupations requiring manual/physical intensive tasks in personal, food, healthcare services (Peri and Sparber (2009)), as well as, on the opposite end of the education spectrum, among college educated, where they take Science, Technology and Engineering jobs rather than occupations in law, communication, sales and human resources (Peri and Sparber (2011b); Peri et al. (2015)). We will use these complementarity parameters, differentiated by education, in our simulation of Section 6 and show their implications for native wages, as immigration inflows have become smaller and more college intensive during the post-2000 period.

Table 2: Estimates of $\frac{1}{\sigma_{IMMI}}$, by education group

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
	Panel A: 1960-2019			
Men, Rel. hours (IV) - No HS diploma	0.063***	0.064***	0.066***	0.069***
	(0.010)	(0.007)	(0.011)	(0.007)
Men, Rel. hours (IV) - HS diploma	0.030***	0.039***	0.037***	0.047***
	(0.010)	(0.007)	(0.010)	(0.006)
Men, Rel. hours (IV) - Some college	0.027**	0.038***	0.036***	0.049***
	(0.011)	(0.007)	(0.011)	(0.006)
Men, Rel. hours (IV) - College degree	0.063***	0.051***	0.077***	0.064***
	(0.012)	(0.008)	(0.013)	(0.006)
	Panel B: 2000-2019			
Men, Rel. hours (IV) - No HS diploma	0.126***	0.119***	0.040	0.072***
	(0.037)	(0.033)	(0.034)	(0.025)
Men, Rel. hours (IV) - HS diploma	0.012*	0.013***	0.015**	0.020***
	(0.007)	(0.005)	(0.008)	(0.004)
Men, Rel. hours (IV) - Some college	0.026***	0.029***	0.033***	0.038***
	(0.006)	(0.005)	(0.007)	(0.004)
Men, Rel. hours (IV) - College degree	0.096***	0.094***	0.106***	0.107***
	(0.008)	(0.006)	(0.009)	(0.006)
Weights	Yes	No	Yes	No
Experience FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No

Notes: In each panel, each set of 4 column-specific coefficients pertains to a different regression. The outcome variable is (log) relative weekly wage for men. Coefficients are 2SLS estimates on the interaction of (log) relative hours worked with 4 education dummies (no high school diploma, high school diploma, some college education, college degree or more), where (log) relative hours are instrumented by (log) relative population. Cell employment is used as weight. Robust standard errors are clustered at the cell level (education by experience).
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

3.2 The native employment-population ratio response

The imperfect substitution between immigrants and natives within skill group, shown in the previous section, suggests that the marginal productivity of natives may increase, on average, in response to inflows of immigrants. The wage effects of immigration, however, are only part of the potential labor market effects. Some recent studies (Dustmann et al. (2017); Amior (2020)) focusing on the impact of immigration on local employment, have emphasized possible displacement or crowding out effects. In particular, these papers find that natives are less likely to migrate to local economies where there are high inflows of immigrants from other local economies within the US.

Such a mechanism could certainly be at work at the local level. However, in analyzing national effects, as in this study, we internalize mobility across locations for each skill group. We note that once one accounts for local adjustments, employment effects may be very different. Additionally, the possible employment effects of cross-location complementarities of workers, driven by internal mobility and internal trade, would not be captured by area analysis but are captured by our national analysis.

To test this, we analyze whether competition effects of immigrants manifest themselves through a decrease in natives' employment-population ratio in the same skill group at the national level. The wage results shown in the previous section suggest increased marginal productivity of natives in response to immigrants, and therefore they are compatible with an *increase* (rather than a decrease/crowding out) of the employment-population ratio nationally. Better productive opportunities and higher marginal value of their labor could have drawn more natives into the labor force and employment. This channel is missing from the analysis and discussion in Ottaviano and Peri (2012), as well as in papers by Manacorda et al. (2012) and Borjas (2003).

To obtain a complete picture of the national effect of immigrants on native labor, therefore, we estimate panel equation (9) where changes in native employment-population ratio depend on changes of immigrant employment (instrumented by changes in their population). Table 3 shows the effect of immigration on native employment rate, using specifications similar to columns (2), (3), (6) and (7) of Table 1 above. The explanatory variable in this case is simply (log) employment of immigrants in a skill cell, instrumented by (log) immigrant population, and the dependent variable is the employment-population ratio of natives in the same cell. The estimates for the 1960-2019 period, reported in Panel A, are highly statistically significant and around 0.06 in the pooled (men and women) specification. This implies that an increase of immigrants by 10 log points (about 10%) in a cell increased the employment-population ratio of natives by 0.6 percentage points. The effect is estimated to be similar, possibly marginally smaller, for the period 2000-2019. Panel B shows very significant estimates mostly around 0.05-0.06.

These estimates highlight two very important points. First, they are consistent with, and confirm, the native-immigrant complementarity shown by the complementarity estimates in the wage regressions. As the labor supplied by natives becomes more valuable due to complementarity with the immigrant labor, natives become more willing to supply labor in the long run and therefore their employment-to-population ratio increases while the share of non-employed among natives decreases. An important reason for this complementarity can be the occupation specialization and occupation upgrading of natives in response to immigration. We will investigate and test for this channel in Section 5. Second, this result shows no evidence that, at the national level, immigration is associated with employment displacement, or crowding out of natives. While this result does not rule out local adjustments of native employment to immigrants, it suggests that over the five-year horizon (as used in the Panel B estimates) these adjustments result in higher national level employment in response to immigrants with similar skills. We show in Section 5 that occupation reallocation takes place in response to immigration, and this may entail geographic mobility as well (or modification of geographic patterns for natives). As these adjustments occur, our estimates imply that at the national level, on average, both employment and wages of native workers increase in response to immigration.

One important caveat is that we analyze aggregate labor markets and not individual workers' outcomes which are not observable in our data. Some individuals may be displaced from work or experience reduced wages due to the competition of immigrants. The differences in individual outcomes and outcomes for the aggregate labor market in response to immigration were also pointed out in Dustmann et al. (2017) and Foged and Peri (2016). Still, our average outcomes suggest that for any group of native workers dropping out of employment or experiencing lower wages from immigration, a larger group of natives are attracted into employment or experiencing increased wages.

Table 3: Effect on native employment-to-population ratio

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
		Panel A: 1960-2019		
Men, Imm. employment (IV)	0.070***	0.078***	0.071***	0.072***
	(0.006)	(0.006)	(0.008)	(0.008)
Women, Imm. employment (IV)	0.078***	0.080***	0.112***	0.109***
	(0.010)	(0.012)	(0.012)	(0.012)
Pooled, Imm. employment (IV)	0.060***	0.060***	0.064***	0.062***
	(0.009)	(0.009)	(0.006)	(0.006)
F-stat (rows 1-3)	4280.41	3516.58	1779.85	1860.60
		Panel B: 2000-2019		
Men, Imm. employment (IV)	0.052***	0.052***	0.063***	0.050***
	(0.008)	(0.006)	(0.011)	(0.014)
Women, Imm. employment (IV)	0.048***	0.044***	0.063***	0.045***
	(0.008)	(0.010)	(0.014)	(0.014)
Pooled, Imm. employment (IV)	0.048***	0.047***	0.056***	0.045***
	(0.007)	(0.007)	(0.009)	(0.011)
F-stat (rows 4-6)	2117.50	1494.85	1735.53	538.80
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Each coefficient of the table is a 2SLS estimate from a different regression. The ratio between native employment and native population (for men, women, or pooled, depending on the row) is the outcome variable, and (log) immigrant employment is the main regressor, which we instrument with (log) immigrant population. Cell employment is used as weight. Robust standard errors are clustered at the cell level (education by experience).
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

4 Reducing omitted variable bias: IV estimation

The estimates in Ottaviano and Peri (2012), as well as those presented in the other studies using a similar approach (Manacorda et al. (2012); Borjas (2003); Borjas and Katz (2007); Borjas, Grogger, and Hanson (2012)) did not go beyond Least Squares panel estimation of equation (8). They relied on the inclusion of large sets of fixed effects to control for the correlation of the error term (productivity changes) with the explanatory variable (labor employment).

Skill-cell-specific productivity shocks which may have initially attracted immigrants to the country and were beneficial to native and immigrant wages may induce a spurious correlation between relative wages and immigrant labor supply in a cell. This would generate a positive or negative bias depending on whether they affected the productivity of immigrants in the skill cell more or less than that of natives. Identifying variation in immigrant population that is less correlated with non-observable skill-specific productivity shocks can reduce such omitted variable bias.

The literature analyzing the effects of immigration across US locations (labor markets) has identified "supply-driven" variation in immigrant population across areas through the use of a shift-share IV approach (Card (2009); Goldsmith-Pinkham et al. (2020)). This method uses the variation in immigrant presence from different countries of origin across US locations, in a period well before the beginning of the analysis, and leverages the large changes in flows of immigrants from specific origins, by decade, to build variation in location-specific immigration flows that is exogenous to local economic trends. While in this context we cannot employ the same approach based on local networks, we adapt the idea of persistent characteristics of immigrants from each country of origin (in our case, in their education and age characteristics) interacted with the (changing) flows by origin over time to construct a shift-share instrument capturing the variation in labor supply of immigrants across skill cells. Additionally, we employ an IV for the population variation of natives across skill cells, whose changes are predicted by projecting age groups forward over decades, for given education structure of the population. Such variation is also driven by population (supply) and not by employment changes.

4.1 A new shift-share IV for cell-specific immigrant labor supply

Immigrants to the US originating from different countries differ significantly in several characteristics. Age and schooling are two of the main ones. For instance, while Mexican and Central American immigrants typically migrated to the US at a very young age (mainly between 20 and 35 years old) and they exhibited low levels of schooling (typically less than high school diploma), immigrants from India tend to move when they are slightly older (between 30 and 40) and tend to be highly educated (with a college degree or more). Chinese immigrants, on the other hand, are distributed more uniformly across education groups.

The different composition is driven, in part, by different selection mechanisms into immigration due to different monetary gains across groups which depend on persistent differences in earnings distribution between the origin and the US, as predicted by a Roy model (Borjas (1987)) and shown in Ambrosini and Peri (2012) and Grogger and Hanson (2011).

Inspired by this observation, we introduce a shift-share approach that considers the distribution of origin-specific flows of immigrants by education and experience cells, using the pre-1980 period, and allocates the more recent inflows from each origin across skill cells in the US labor market proportional to that pre-determined distribution. The changing pattern of countries of origin over decades generates the variation of labor supply across skills. For instance, if, as it was the case, Mexican immigration declined in the post-2000 period while immigration from India increased, this would be associated to a decline in the labor supply for low age-low education cells, and an increase in labor supply for the middle-age, high-education cells.

Specifically, we compute net flows of immigrants between 1960 and 1980 (the pre-1980 period) for each country of origin. We consider individually the top 5 sending countries, aggregating all others by continent.[9] This leaves us with 12 selected origins: the 5 top countries - i.e., Mexico, Cuba, China, Philippines and Korea - and 7 continents - i.e., North America, Central America and Caribbean, South America, Europe, Africa, Asia and Oceania.[10] We then use these 12 groups (henceforth, we will refer to them broadly as countries of origin) to build the cell-based shift-share IV. The share of immigrants from country of origin c, in education k-experience j cell is defined as follows:

$$sh_{kj}^{c} = \frac{\Delta^{80,60} pop_{kj}^{c}}{\Delta^{80,60} pop^{c}} \tag{10}$$

where $\Delta^{80,60} pop$ represents the 1980-1960 net immigration for the group from country of origin c residing in the US. In the numerator the net change is computed for each individual skill cell, while the change in the denominator aggregate the whole net immigration from country c. With 32 cells for each country of origin (4 education cells by 8 experience cells), we encounter a few cases with a negative cell-specific net flow (i.e., negative numerator in (10)). This happens when inflows of individuals from c in a given cell did not compensate outflows (due to return migration or aging into other cells). In those instances, we set the net flows to zero both in the numerator and in the aggregation generating the denominator

[9]We compute the same estimates selecting the top 6 countries, which amounts to including India separately. We do not find any significant difference. Additional details on these flows are reported in Appendix B.

[10]We drop individuals not assigned to a specific country or continent, and those assigned to Antarctica.

of (10). This correction allows us to obtain:

$$sh^c_{kj} \geq 0 \; \forall \{c,k,j\} \text{ and } \sum_{\{k,j\}} sh^c_{kj} = 1 \; \forall c \tag{11}$$

Then, for each country, we compute the aggregate net flows $\Delta^{t,t-10} pop^c$ for each of the four decades from 1980 to 2019, and we use these along with the shares to obtain the country-specific imputed ten-year change for each cell as follows:

$$\widehat{\Delta^{t,t-10} pop}^c_{kj} = sh^c_{kj} * \Delta^{t,t-10} pop^c \qquad \forall t \in \{1990, 2000, 2010, 2019\} \tag{12}$$

The imputed changes from (12), which can be positive or negative depending on the aggregate net flow from each country of origin c in a given decade, are then summed over countries of origin to obtain the imputed foreign-born (F) supply change in each education-by-experience cell:

$$\widehat{\Delta^{t,t-10} pop}^F_{kj} = \sum_c \widehat{\Delta^{t,t-10} pop}^c_{kj} \tag{13}$$

Finally, we compute the predicted cell-specific foreign-born population at time τ, $\forall \tau \in \{1990, 2000, 2010, 2019\}$, which we will use as our instrument for immigrant labor supply measures (in this case, foreign employment), by summing the initial immigrant population of each cell in 1980 to the cumulative imputed supply change of the cell for all decades up to τ as follows:

$$(\widehat{pop^F_{kj}})_\tau = (pop^F_{kj})_{1980} + \sum_{t=1990}^{\tau} \widehat{\Delta^{t,t-10} pop}^F_{kj} \quad \text{with } t \in \{1990, 2000, 2010, 2019\} \tag{14}$$

In $\tau = 1980$ we simply have $(\widehat{pop^F_{kj}})_{1980} = (pop^F_{kj})_{1980}$. We use the measure constructed as in equation (14) to instrument for foreign-born employment.

When we consider the period 2000-2019, we repeat the same procedure, obtaining country-specific imputed changes for 2005 and 2015. We drop observations before 2000, obtaining five imputed 5-year changes (i.e., for 2000, 2005, 2010, 2015 and 2019).[11]

4.2 Demographic change as predictor of native cell supply

As the explanatory variable in equation (8) is the (log of the) ratio of immigrant and native employment, we will instrument the variation of native population across cells, and then take the (log of the) ratio as IV. We proxy for native population change by predicting the de-

[11] As they are cumulative changes, the imputed values for 2000, 2010 and 2019 remain the same as before.

mographic evolution of the native population. Specifically, we forecast native employment of a given group with education level k and years of potential labor market experience j by using previous decade's native population in the group with the same education level k but with experience $j-10$ years. For instance, the native population of the group of individuals with high school degree and 15 years of potential experience in the labor market in 1990 is used to construct the native population for the group with high school degree and 25 years of experience in 2000, and so on.

In so doing, we project the size of each cell forward to the following decade (or 5-year period when considering the 2000-2019 interval), adding 10 (or 5) years to their experience group, while leaving the education structure unchanged. Since for the two youngest groups (between 0 and 5, and between 5 and 10 years of potential experience) we cannot impute exact population size from the past, we rely instead on the education structure of the youngest cohort in the previous period. Specifically, we take the total population of natives with years of potential experience 0 to 5 and 5 to 10 in the decade and allocate them across the four education groups using the education shares of the youngest cohort in the labor market observed in the previous decade.[12] We refer to this approach as the *best one decade-ahead prediction* for each cell.

4.3 Power and Validity of the instruments

Once we have constructed the predicted immigrant (foreign-born F) population, $(\widehat{pop^F_{kj}})_t$, with the shift-share method described in Section 4.1, and the predicted native (domestic D) population, $(\widehat{pop^D_{kj}})_t$, with the demographic projections described in Section 4.2, we are ready to build two instruments.

The first, $\ln\frac{(\widehat{pop^F_{kj}})_t}{(\widehat{pop^D_{kj}})_t}$, will be used in equation (8) as an instrument for $\ln\left(\frac{Empl_{Fkjt}}{Empl_{Dkjt}}\right)$ to estimate the parameter $\frac{1}{\sigma_{IMMI}}$; the second, $\ln(\widehat{pop^F_{kj}})_t$ will be used in equation (9) as an IV for $\ln(Empl_{Fkjt})$ to estimate the parameter β_{emp}.

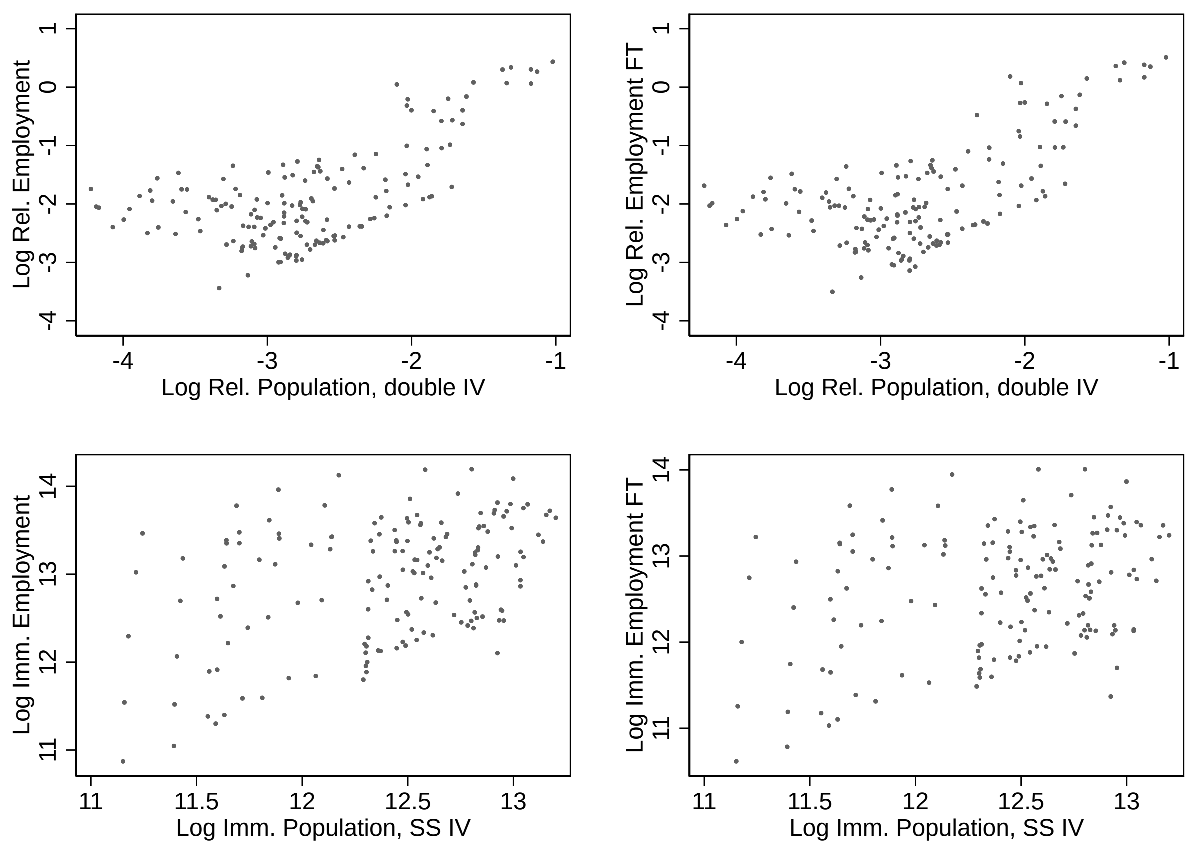
The panels of Figure 4 show the first-stage correlations of the two instruments with the changes in labor supply for the 1980-2019 period. The top left panel shows the raw correlation between the (log of) predicted relative population and (log of) relative employment for all workers, whereas the top right panel shows the same correlation for full-time workers only. A strong positive correlation is visible. This strong raw correlation carries over to the first-stage F statistics reported in column (1) and (3) of Table 5, Panel A and equal to 71.58

[12] Since for the 2000-2019 period we project the size of cells forward by 5 years, rather than 10, we rely on this education-based adjustment only for the youngest group (0 to 5 years of experience) in each period of this interval. Clearly, we do so by using the education shares of the youngest cohort observed 5 years earlier.

and 92.05. Those capture the partial correlation of the IV, after controlling for the fixed effects.

The two bottom panels of Figure 4 show the first-stage raw correlation between the (log of) predicted foreign-born population and (log of) foreign-born employment of all workers (left panel) or of full-time workers only (right panel). A positive correlation is visible, albeit weaker than for the top panels. The F statistics for these first-stage partial correlations from Panel B of Table 5 are 16.19 and 15.86. Overall, the first-stage F statistics for both panels are well above the standard rule of thumb of 10, below which concerns regarding weak instruments emerge.

Figure 4: First-stage relationships for Table 5



Notes: The upper left figure refers to the first-stage relationship for 2SLS coefficients reported in columns (1) and (2) of Panel A. Upper right figure refers to those in columns (3) and (4) of Panel A. Bottom left figure to those in columns (1) and (2) of Panel B. Bottom right figure to those in columns (3) and (4) of Panel B.

The panels of Figure 5 show the same first-stage correlations as in Figure 4, but are constructed for the more recent period 2000-2019 and for the relative changes in labor supply. The top panels show the raw correlation between the (log of) imputed population ratio and the (log of) employment ratio, including all workers in the left panel and full-time only in the right one. The bottom panels show the correlation between the (log of) foreign-born employment and the (log of) imputed foreign-born population, again including all workers in the left panel and full-time workers only in the right. Visual inspection of the raw correlations in Figure 5 reveals a positive but a bit weaker correlation of the IV with (log of) immigrant employment, and a strong correlation of the IV with relative employment. Table 6 shows that the power to predict the (log of) relative employment is, in fact, somewhat weaker after controlling for the fixed effects (F statistics between 22 and 31) while IV predicting the (log of) foreign-born employment are a bit stronger (F statistics 30 to 36). Nevertheless, in this case as well, the first-stage F statistics of both panels exceed the conventional threshold, reassuring us against the presence of weak instruments.

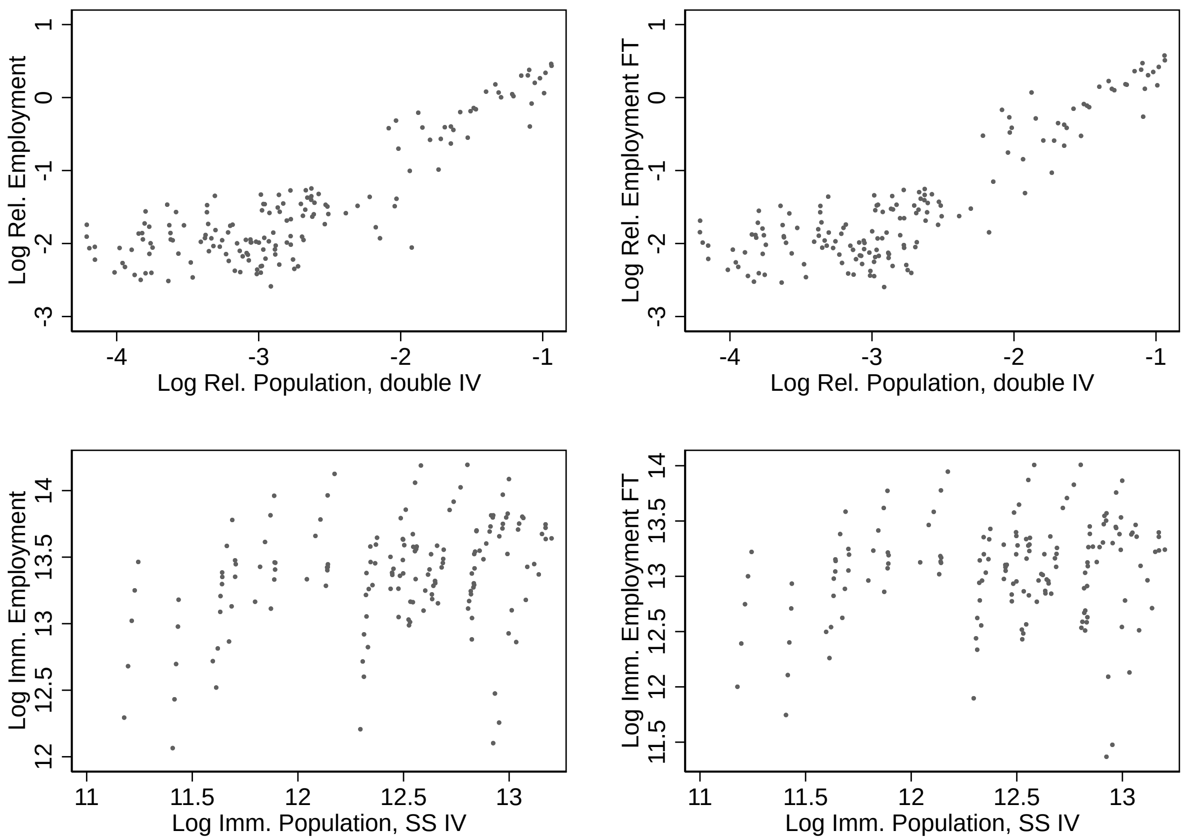
As our regressions feature a single endogenous regressor, we can consider the relative asymptotic bias test for weak instruments by Olea and Pflueger (2013), more appropriate in presence of clustered errors. Conducting the test at the 5% confidence level, our "effective" F statistics reported in the tables surpass the critical value of 23.1 for 2SLS with a worst-case bias of 10%. Despite this more stringent threshold, if compared to the standard Stock-Yogo critical values for the i.i.d. case, we can confidently reject the null hypothesis of weak instruments for almost all our regressions of Tables 5 and 6, except for those in Panel B of Table 5, which should therefore be taken with a bit of caution.

In adopting a shift-share type of IV as we do, which is based on past skill-specific patterns combined with changing immigration flows by country of origin, it is important to test that the components of the IV are not driven by a correlation with past cell-specific labor market trends, which may persist and affect wages and employment in the post-2000 period.[13] Previously, we noted that aggregate inflows of immigrants changed significantly after 2000 with large declines of Mexicans and increases in Asians. These new flows produce the post-2000 variation of our IV and, since we newly estimate the post-2000 native-immigrant complementarity and the related effects of immigration, we test that they are uncorrelated with trends, specific to skill cells before 2000.

To check these correlations we proceed as follows. First we submit them to visual inspection by plotting them in the two panels of Figure 6. In the upper panel, we show the correlation of the 2000-2019 changes in the (log of) relative-population IV (horizontal axis) with the 1980-1990 and 1990-2000 stacked changes in the (log of) relative wage (vertical axis), after controlling for education and decade dummies. The units of observations are education-experience cells. In the bottom panel, instead, we show the scatterplot of the 2000-2019 changes in the (log of) immigrant-population IV (horizontal axis) against the

[13] This is a more direct test of lack of correlation with pre-trends for the IV, rather than one focused only on the more relevant "shares" of immigrants as in Goldsmith-Pinkham et al. (2020).

Figure 5: First-stage relationships for Table 6



Notes: The upper left figure refers to the first-stage relationship for 2SLS coefficients reported in columns (1) and (2) of Panel A. Upper right figure refers to those in columns (3) and (4) of Panel A. Bottom left figure to those in columns (1) and (2) of Panel B. Bottom right figure to those in columns (3) and (4) of Panel B.

1980-1990 and 1990-2000 stacked changes in native employment-population ratio (vertical axis), controlling for education and decade dummies. Both panels plot the correlation of residuals of these changes, both unweighted (black diamond markers) and weighted (circles, whose size is proportional to cell employment in 1980, which we use as weight). We display on the chart the corresponding LS regression lines (dotted for the unweighted regression, dashed for the regression with weights) and the LS coefficients (capturing by the slope) with their p-values.

Both panels of Figure 6 show visually, and confirm statistically, the absence of a significant relationship, suggesting that IV-imputed population changes after 2000 are not correlated with wages and native employment changes before 2000. This evidence is shown more systematically in Table 4, where we report the LS estimates of regressions of changes in outcomes (1980-1990 and 1990-2000, stacked) on the IV-imputed population changes (2000-

2019). The outcome for columns (1) to (4) are (log of) relative wage, while for columns (5) to (8) they are native employment-population ratio. Columns (1), (2), (5) and (6) do not include dummies, while column (3), (4), (7) and (8) control for education and decade dummies (4 education groups and 2 decades). The estimates, some of which were visualized in Figure 6, are never significant at the 5% confidence level, and only one coefficient out of eight is marginally significant at the 10% level.[14]

Table 4: Instrument validity - OLS estimates of the effect of IV on pre-trends in outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ Wage	Δ Wage	Δ Wage	Δ Wage	$\Delta\frac{Emp}{Pop}$	$\Delta\frac{Emp}{Pop}$	$\Delta\frac{Emp}{Pop}$	$\Delta\frac{Emp}{Pop}$
ΔIV_{00-19} (SS + demogr.)	0.021	0.038*	0.014	0.032				
	(0.015)	(0.019)	(0.016)	(0.019)				
ΔIV_{00-19} (SS)					0.016	0.024	-0.078	-0.064
					(0.021)	(0.021)	(0.047)	(0.045)
Constant	-0.006	-0.011*	0.009	0.001	0.011***	0.011***	-0.031***	-0.031***
	(0.005)	(0.006)	(0.014)	(0.015)	(0.003)	(0.003)	(0.006)	(0.006)
Observations	64	64	64	64	64	64	64	64
R-squared	0.035	0.075	0.115	0.152	0.003	0.006	0.701	0.670
Weights	No	Yes	No	Yes	No	Yes	No	Yes
Education FE	No	No	Yes	Yes	No	No	Yes	Yes
Decade FE	No	No	Yes	Yes	No	No	Yes	Yes

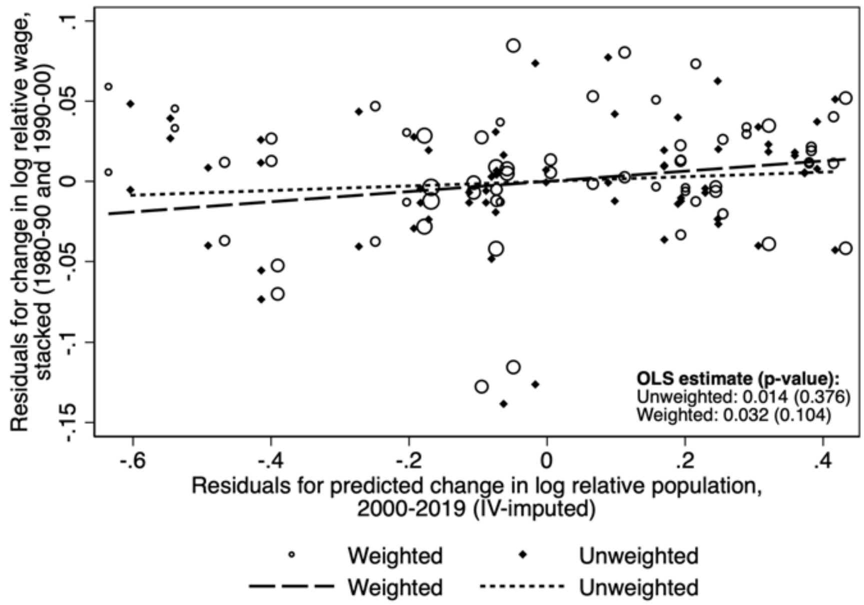
Notes: The table reports OLS estimates for regressions of stacked changes for 1980-1990 and 1990-2000 in outcome of interest (log relative wage in the first four columns, and native employment-population ratio in the last four columns) on the 2000-2019 changes in the corresponding IV-imputed population measure (log relative population and log immigrant population, respectively). Observations are education-experience cells. Cells are weighted by 1980 employment. Robust standard errors are reported in parentheses.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

In conclusion the constructed IV exhibits reasonable power and passes validity tests as it is uncorrelated with pre-2000 trends. Next, we proceed to use our IV to estimate the parameters of interest.

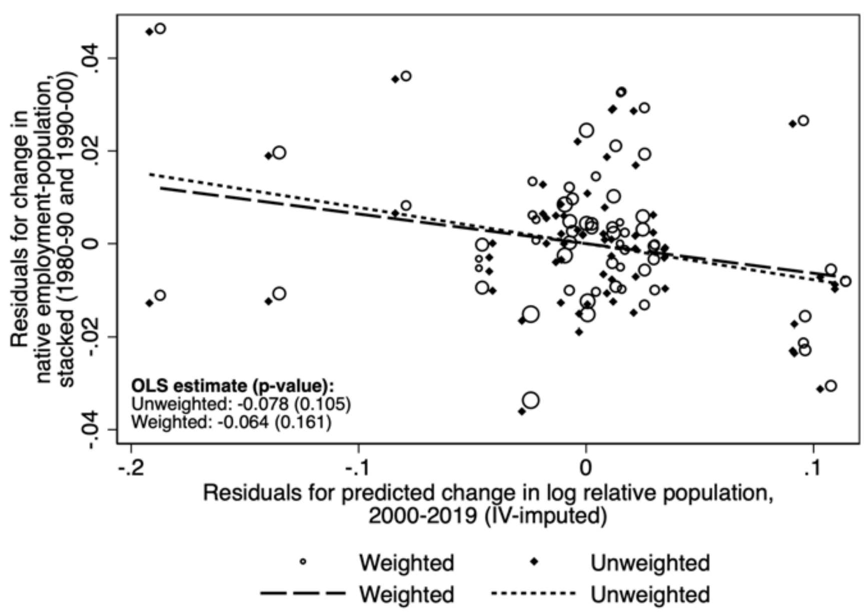
[14]Including fixed effects as we do in all our specifications seems to help absorb the small correlation between IV and pre-2000 relative wages, which is displayed in Appendix Figure 7.

Figure 6: Pre-trends in outcomes

(a) Relative wage



(b) Native employment-population ratio



Notes: This figure plots the correlation between residual changes in outcomes of interest before 2000 and residual changes in corresponding IV measures after 2000 by skill cell, after controlling for education and decade dummies. The upper (lower) panel displays residuals for 1980-1990 and 1990-2000 stacked changes in log relative wage (native employment-population ratio) and residuals in IV-imputed changes for 2000-2019 in log relative population (log immigrant population) by skill cell. OLS estimates from regressions of residual changes in outcomes on residual changes in IV measures (and corresponding p-values) are reported. Unweighted regressions are represented by the dotted lines (pertaining to the black diamond markers), while weighted regressions are given by the long-dashed lines (circles). Circle sizes are proportional to 1980 cell employment (used as weight).

4.4 2SLS estimates

Tables 5 and 6 present our IV results. Panel A presents estimates of $\frac{1}{\sigma_{IMMI}}$, which captures native-immigrant productive complementarity. Panel B shows the estimates for the coefficient β_{emp}, which captures the potential crowding out or crowding in of immigration on native employment-population ratio. All specifications use 2SLS estimation method controlling for skill-cell-effects and year-effects. The sample used in rows (1) to (3) of each panel includes men, women, and a pooled sample, respectively, in constructing the outcome variable. Table 5 is estimated over the period 1980-2019, while Table 6 only includes data for the more recent decades (2000-2019). The column estimates differ due to weighting (columns (1) and (3)) or not weighting (columns (2) and (4)) by the cell employment, and by worker sample (include all workers in the estimation of (1) and (2), or full-time workers only in (3) and (4)).

Overall, the key results from the Least Squares estimations are confirmed in these specifications with a few differences. First, the intensity of complementarity between immigrants and natives is weaker in the 2SLS estimates for the 1980-2019 period, especially for men. The coefficient is not significant for men, and is significant in half of the cases for women and the pooled sample, with a magnitude between 0.03 and 0.05. However, the estimates of Table 6 show that the same coefficient estimated on the two most recent decades is larger and mostly statistically significant. Its value is between 0.05 and 0.06 when estimated on the pooled sample. While the 2SLS estimates have a somewhat larger standard error (around 0.025) relative to OLS (around 0.01), most estimates in Table 6 reveal imperfect substitutability and an elasticity between natives and immigrants around $18-20$ for the period 2000-2019, consistent with the original results in Ottaviano and Peri (2012). The weaker complementarity estimates for the 1980-2000 period, when more low-educated immigrants arrived in the US, and the higher complementarity estimates in the post-2000 period are consistent with the important role of highly educated immigrants in generating differentiation and complementarity with natives.

The second important result is that both Panel B of Tables 5 and 6 reveal a significant positive response of employment-population ratio of natives to immigration. Skill cells experiencing a higher inflow of immigrants exhibited crowding in of natives, whose employment-population ratio increased significantly. The estimates vary somewhat depending on the sample, the period and the specification, ranging from 0.04 to 0.21 and are always statistically significant at the 5% level (and in most cases at the 1%). The estimates for the more recent period, 2000-2019, for the pooled sample are between 0.048 and 0.095, which is also consistent with the Least Squares estimates. We will use those as reference values.

The estimated positive effects on employment-population ratio are in contradiction with some local estimates that suggest crowding out of natives in response to immigration at the local level (Dustmann et al. (2017); Amior (2020)).[15] There are several reasons why the complementary effects of immigrants can be stronger in the aggregate national market than locally. First, adjustments through occupational reallocation and national response to higher demand from immigrants are likely to spill over outside the local economy and to imply reallocation of workers across commuting zones. The national approach, as predicated by its early advocates such as Borjas (2003), may be a better approach to internalize those effects and produce estimates that are more useful in evaluating the aggregate impact of immigrants on employment and wages. Additionally, our framework is much more careful in differentiating among workers' skills and substitutability-complementarity patterns, rather than considering labor as one type of undifferentiated workers (as in Amior (2020)). While we think the local analysis sheds light on important mechanisms, we also think that the present framework, focused on a national analysis across skill groups, both complements local analysis work and is better suited to infer national labor market effects of immigration.

In Table 7 we push our estimates relative to 2000-2019 a step further. We showed in Section 3, using an simple population instrument, that for different education groups the intensity of complementarity between immigrants and natives was different, with more intense complementarity among the college educated and the no-high-school-degree groups. In this table, we interact both the explanatory variable and the instrument with education-group dummies, providing the counterpart based on our refined IV approach to the education-specific estimates of Table 2. In particular, we estimate a different coefficient for each of the four education groups. Table 7 shows the results for the wage complementarity coefficients (Panel A) and for the employment-population ratio coefficients (Panel B). Since these regressions feature more than one endogenous explanatory variable, caution is needed. Table 18 in Appendix B reports several test statistics used to detail the nature of any weak-instrument problem concerning Table 7. In particular, it provides Shea's partial R^2, which generalizes the standard partial R^2 for cases with more than one endogenous regressor. While there is no consensus on what value indicates a problem, values for Panel A look sufficiently high and do not indicate the existence of a serious issue. Table 18 also provides first-stage F statistics and the Sanderson–Windmeijer corrected conditional F statistics for first-stage regressions of each endogenous regressor. The sizes of these statistics do not indicate a weak-instrument problem as they appear to be larger than Stock-Yogo critical values, even though their use is questionable as our models feature robust standard errors. We also report the Kleibergen-Paap statistic, a robust version of the Cragg–Donald minimum eigenvalue statistic, which

[15] Older studies on US local economies, such as Basso and Peri (2015) and Peri and Sparber (2011a), however, did not find significant crowding out.

Table 5: 2SLS estimates for elasticity of substitution and labor supply effect, 1980-2019

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Elasticity estimates (1980-2019)				
Men, Rel. employment (SS IV + demogr. IV)	-0.009	-0.007	0.008	0.009
	(0.023)	(0.020)	(0.021)	(0.018)
Women, Rel. employment (SS IV + demogr. IV)	0.033	0.049**	0.030	0.041**
	(0.024)	(0.020)	(0.022)	(0.017)
Pooled, Rel. employment (SS IV + demogr. IV)	0.018	0.020	0.030*	0.030**
	(0.020)	(0.016)	(0.018)	(0.015)
F-stat (rows 1-3)	71.58	75.80	92.05	96.08
Panel B: Labor supply estimates (1980-2019)				
Men, Imm. employment (SS IV)	0.100***	0.080***	0.152***	0.086**
	(0.029)	(0.025)	(0.043)	(0.035)
Women, Imm. employment (SS IV)	0.063**	0.031	0.215***	0.098*
	(0.025)	(0.021)	(0.074)	(0.050)
Pooled, Imm. employment (SS IV)	0.056***	0.040**	0.114***	0.057**
	(0.020)	(0.018)	(0.040)	(0.026)
F-stat (rows 4-6)	16.19	18.48	15.86	18.38
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Panel A reports 2SLS estimates for the immigrant-native elasticity of substitution. Relative weekly wage in log (for men, women, or pooled) is regressed on relative employment, which is instrumented with the imputed relative population, a ratio of instruments. We adopt a shift-share IV approach to impute the numerator (foreign-born population), while we use a demographic instrument for the denominator (native population). Panel B reports 2SLS estimates from regressions of native employment-population ratio (for men, women, or pooled) on immigrant employment in log, which is instrumented with immigrant population imputed with the same shift-share IV approach as in Panel A. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience).
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

provides an overall test of weak instruments (Cameron and Trivedi (2022)).

In terms of complementarity coefficients, Panel A of Table 7 confirms the results of Section 3. The specifications estimated on the sample of all workers (columns (1) and (2)) show coefficients in the order of 0.1 for the most and least educated groups, while they are 0.02-0.04 for the two intermediate groups. The estimated effects on the employment-population ratio are more similar across education groups and around 0.04-0.06. As for the specification using full-time workers only, the complementarity coefficients on less educated are a

Table 6: 2SLS estimates for elasticity of substitution and labor supply effect, 2000-2019

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Elasticity estimates (2000-2019)				
Men, Rel. employment (SS IV + demogr. IV)	0.035	0.026	0.041	0.029
	(0.027)	(0.029)	(0.026)	(0.027)
Women, Rel. employment (SS IV + demogr. IV)	0.073**	0.063**	0.068**	0.058**
	(0.028)	(0.025)	(0.029)	(0.023)
Pooled, Rel. employment (SS IV + demogr. IV)	0.058**	0.050**	0.059**	0.049**
	(0.025)	(0.025)	(0.025)	(0.023)
F-stat (rows 1-3)	22.42	13.37	31.62	17.25
Panel B: Labor supply estimates (2000-2019)				
Men, Imm. employment (SS IV)	0.076***	0.065***	0.078***	0.047***
	(0.008)	(0.007)	(0.015)	(0.014)
Women, Imm. employment (SS IV)	0.082***	0.053***	0.140***	0.056**
	(0.022)	(0.017)	(0.051)	(0.025)
Pooled, Imm. employment (SS IV)	0.075***	0.057***	0.095***	0.048***
	(0.013)	(0.011)	(0.027)	(0.015)
F-stat (rows 4-6)	36.14	75.37	30.21	58.49
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Panel A reports 2SLS estimates for the immigrant-native elasticity of substitution. Relative weekly wage in log (for men, women, or pooled) is regressed on relative employment, which is instrumented with the imputed relative population, a ratio of instruments. We adopt a shift-share IV approach to impute the numerator (foreign population), while we use a demographic instrument for the denominator (native population). Panel B reports 2SLS estimates from regressions of native employment-population ratio (for men, women, or pooled) on immigrant employment in log, which is instrumented with immigrant population imputed with the same shift-share IV approach as in Panel A. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience).
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

bit smaller, but those on employment-population ratio are larger for all workers. The employment effects of complementary immigrants may have been stronger in pushing natives towards full-time jobs, especially among highly educated individuals.

The refinements and extensions of the Ottaviano and Peri (2012) estimates discussed in this section have confirmed three crucial features of the productive interactions of immigrants and natives in the long run. First, even when these two groups have similar education and age, their employment in the labor market shows a significant degree of complemen-

Table 7: 2SLS estimates breaking down by education

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Elasticity estimates (2000-2019)				
Pooled, Rel. employment - No HS diploma	0.115***	0.101***	0.025	0.052**
	(0.031)	(0.025)	(0.042)	(0.025)
Pooled, Rel. employment - HS diploma	0.017***	0.015***	0.018***	0.018***
	(0.006)	(0.005)	(0.005)	(0.004)
Pooled, Rel. employment - Some college	0.041***	0.040***	0.044***	0.046***
	(0.005)	(0.004)	(0.004)	(0.003)
Pooled, Rel. employment - College degree	0.104***	0.098***	0.112***	0.107***
	(0.008)	(0.006)	(0.008)	(0.006)
Panel B: Labor supply estimates (2000-2019)				
Pooled, Imm. employment - No HS diploma	0.029	0.039*	0.132**	0.154***
	(0.022)	(0.021)	(0.061)	(0.036)
Pooled, Imm. employment - HS diploma	0.043*	0.053**	0.149**	0.171***
	(0.022)	(0.022)	(0.062)	(0.037)
Pooled, Imm. employment - Some college	0.047**	0.057***	0.153**	0.176***
	(0.022)	(0.022)	(0.063)	(0.037)
Pooled, Imm. employment - College degree	0.049**	0.059***	0.154***	0.176***
	(0.022)	(0.021)	(0.060)	(0.035)
Weights	Yes	No	Yes	No
Experience FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No

Notes: This table expands upon Table 2. Coefficients reported are 2SLS estimates. In each panel, each set of 4 column-specific coefficients pertains to a different regression, which includes 4 endogenous variables and 4 instruments. In Panel A, the outcome variable is pooled (log) relative weekly wage, while the endogenous variable is the interaction of (log) relative employment with 4 education dummies (no high school diploma, high school diploma, some college education, college degree or more), instrumented with the interaction between (log) relative population imputed using our shift-share IV approach for foreign-born and a demographic IV for natives and the 4 education dummies. In Panel B, the outcome variable is the pooled native employment-population ratio, while the endogenous variable is the interaction of (log) immigrant employment with 4 education dummies (no high school diploma, high school diploma, some college education, college degree or more), instrumented with the interaction between (log) immigrant population imputed using a shift-share IV approach and the 4 education dummies. Cell employment is used as weight. Robust standard errors are clustered at the cell level (education by experience).
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

tarity, implying that they do not compete for same jobs, but rather the employment of one group helps the productivity of the other. Second, these synergies/complementarities are strong in the group of workers with no high school degree, and even stronger for workers with college degree or more. Recalling that the latter group was also the fastest-growing group of immigrants in the last 20 years, it is unsurprising that the complementarity between immigrants and natives seems to have increased post-2000. Third, this complementarity is consistent with immigrants generating productive opportunities for natives and attracting them in the labor market. As we have shown, the employment-population ratio of natives has responded positively to the inflow of immigrants in the last 20 years. Overall, these complementarities appear significant and seem to have grown stronger over the last two decades.

5 Effects on occupational upgrading

What mechanisms help generate the complementarity and positive employment effects of immigration on natives of similar education and experience? One natural candidate for explaining these effects is specialization in different/complementary occupations along the lines of comparative advantages. Occupational separation of natives and immigrants is a feature identified in local economies by a series of papers (e.g., Peri and Sparber (2009, 2011b); Cattaneo, Fiorio, and Peri (2015)), and occupational upgrading of natives in response to immigration – as discussed in existing literature (Peri and Sparber (2009); Foged and Peri (2016)) – can be a mechanism contributing to these results.

To investigate these mechanisms in our setting, we ask whether immigration shifted the cell-specific occupational distribution for natives towards occupations that pay more (and in which they have comparative advantages). As described in Section 1, we construct a measure of "occupational quality" by associating each occupation with the average national weekly wage paid to workers in 1980. Then we weight these occupational wages by the share of native workers employed in each occupation, within each education k-experience j cell in each considered year t. A shift of natives towards occupations with higher weekly wages (i.e., upgrading), over the years, implies an increase in this "occupational quality" measure. In Table 8 we report the 2SLS estimates of coefficient β_{occ} from the following regression:

$$\ln(Occ\ Index_D)_{kjt} = \phi_{kj} + \phi_t + \beta_{occ} \ln\left(Empl_{Fkjt}\right) + e_{kjt} \tag{15}$$

where $(Occ\ Index_D)_{kjt}$, as described above, is equal to $\sum_{Occ}\left((Share_{occ})_{Dkjt} x (Wage_{occ})_{Dkj,1980}\right)$, the employment share-weighted occupation wage in 1980 for domestic workers in cell of education k and experience j. The occupation shares sum to one within each education-experience cell in each year. This definition implies that changes in the index are solely driven by changes of native worker shares within a skill group across occupations, with a positive change indicating a movement towards higher-quality/higher-paying occupations (based on 1980 wage data), on average.

Table 8 presents the estimates of coefficient β_{occ} from equation (15) above. The table follows the same structure and specifications (in its rows and columns) as the previous tables,

Table 8: 2SLS estimates on occupational quality of natives

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
	Panel A: Occupational quality estimates (1980-2019)			
Men, Imm. employment (SS IV)	0.071***	0.054***	0.060***	0.039***
	(0.018)	(0.015)	(0.014)	(0.012)
Women, Imm. employment (SS IV)	0.054**	0.027	0.043**	0.007
	(0.022)	(0.017)	(0.018)	(0.015)
Pooled, Imm. employment (SS IV)	0.036***	0.030***	0.022***	0.017***
	(0.010)	(0.008)	(0.007)	(0.006)
F-stat (rows 1-3)	16.19	18.48	15.86	18.38
	Panel B: Occupational quality estimates (2000-2019)			
Men, Imm. employment (SS IV)	0.037***	0.030***	0.026***	0.019***
	(0.006)	(0.004)	(0.005)	(0.003)
Women, Imm. employment (SS IV)	0.015	0.002	0.008	-0.007
	(0.010)	(0.006)	(0.012)	(0.006)
Pooled, Imm. employment (SS IV)	0.020***	0.018***	0.009	0.010***
	(0.005)	(0.003)	(0.008)	(0.003)
F-stat (rows 4-6)	36.14	75.37	30.21	58.49
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Both panels report 2SLS estimates from regressions where the outcome variable is a measure of native occupational quality (for men, women, or pooled, depending on the row). We regress this variable on (log) immigrant employment, which is instrumented with immigrant population imputed with our shift-share IV approach. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience).
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

separating rows by gender and columns by worker status. We show weighted (odd columns) or unweighted (even columns) regression results. Finally, Panel A displays the coefficients estimated using decade data for the 1980-2019 period, while Panel B shows the estimates with the five-year data over the more recent 2000-2019 period.

The coefficients of the table are positive and mostly significant, which is consistent with the idea that more immigrants pushed natives into higher-paid occupations, where they likely possess comparative advantages. This occupational upgrading seems to be slightly larger and more significant for men. Considering the pooled estimates, an increase of immigrants by 10 log points in a skill cell (about 10%) increased the occupational quality (wage) of natives in that cell by 0.2 to 0.3%, using the 1980-2019 estimates, or by 0.1 to 0.2%, using the more recent period. This reallocation to occupations with higher wages is consistent with the increased labor participation among natives and with the positive complementarity effect estimated in the previous sections. The type of job reallocation that we see taking place at the occupation level may also be happening at a finer level (for example, within occupations), with natives moving to tasks that are complementary to those performed by immigrants. Our data, however, lack the granularity needed to test this mechanism.

6 Simulated effects of immigration on native wages and employment rates: 2000-2019 and 2019-2022

In this section we return to the model described in Section 2. Using the parameter $1/(\sigma_N)$, newly estimated among the more recent sample (2000-2019) and with more current econometric methods (IV using shift-share and demographic predictions), in combination with other standard elasticity parameters taken from the literature (including Ottaviano and Peri (2012), Card and Lemieux (2001), Katz and Murphy (1992), Goldin and Katz (2009) and Autor et al. (2020)), we estimate the effects of changing the supply of immigrants in each skill group on wages of natives by skill group. In particular, we first equate the marginal productivity of each type of workers to their wages, obtaining a wage equation for each native worker (denoted as usual by D) of education group k and experience j. Then we take a total differential of the log of the native wage w_{Dkj} with respect to the supply of immigrants in each group ($\frac{\Delta L_{Fkj}}{L_{Fkj}}$). The corresponding formula obtained from this procedure is shown and described in Appendix C, by equation (16). Using the estimated elasticity values, the wage bill share for each skill group, and the percentage change in supply of foreign-born in each skill group, we can then calculate these effects of changing immigrants supply on natives' wages.

We present results grouped by native workers' education level. First, we consider the wage responses (averaged across age groups) to changes in immigrants for the 2000-2019 period. Results of these simulations are shown in columns (1) to (4) of Table 9. Columns (1) to (4) of Table 10, then show the wage effect on natives of the inflow of immigrants during the very recent 2019-2022 period. Table 9 and Table 10 follow a similar structure. The differences across the simulations of columns (1) to (4) are due to the choice of elasticity parameters, which are taken from their estimated values. The values used in each simulation are reported in the bottom six rows of the tables. In column (1) the choice of parameter values for the simulation follows the preferred specification of Ottaviano and Peri (2012) in terms of parameters not specific to the immigrant-native interactions. Specifically we set $1/\sigma_{H-L} = 0.54$, $1/\sigma_{EDU,H} = 0.16$, $\sigma_{EDU,L} = 0.03$, and $1/\sigma_{EXP} = 0.16$. We update the value of

$1/(\sigma_N)$, which we impose equal to 0.058 for all groups, reflecting our estimate in Table 6 for the pooled sample of all workers in the specification that uses weights (i.e., the estimate in the third row of column (1) in Panel A of Table 6). In column (2) we leave the set of non-immigration specific parameter values unchanged, but we allow $1/(\sigma_N)$ to differ between more and less educated individuals, using $1/(\sigma_N)_L = 0.045$ for those with a high school degree or less (the average of our estimated coefficients in Table 7), and $1/(\sigma_N)_H = 0.10$ for those with some college education or more (the average value for the estimates in the last row of Table 7). This choice reflects the evidence, supported by most of the estimates in the previous sections, that the complementarity between immigrants and natives among college educated seems stronger than among other groups.

While interpreting the results, we need to bear in mind that the number of college-educated immigrants exhibited the largest growth over the past two decades, while the number of immigrants with no degree has declined.

We test the robustness of our results to alternative configurations in columns (3) and (4). In column (3) we increase the complementarity between broad education groups and set $1/\sigma_{H-L} = 0.71$, the exact estimate from Katz and Murphy (1992). Finally, in column (4), we use $1/\sigma_{EDU,H} = 1/\sigma_{EDU,L} = 0$, implying perfect substitution within broad education group. The standard errors for the $1/(\sigma_N)$ parameters are taken from Tables 6 and 7, while other elasticity values are from the same sources as the estimated parameter.

We proceed as follows. We begin by generating 1,000 extractions for a given configuration of the parameters from a joint normal distribution. Subsequently, using formula (16) from Appendix C, we calculate the wage effect for each education-experience group in response to the same immigration inflow (for 2000-2019, or for 2019-2022) and take the average and the standard deviation of the 1,000 simulated values. Native wage changes for each education group and the overall average (along with their standard errors), as reported in columns (1) to (4) of Tables 9 and 10, are obtained by averaging wage changes of each education-experience group weighting by its share in the 2019 wage bill in the relevant education group or overall.[16]

Three findings emerge from columns (1) to (4) of Table 9. First, due to the relative concentration of new immigrants among college-educated and the complementarity between college- and non-college-educated, the immigrant inflow of 2000-2019 helped the wage growth of less educated natives (those with high school degree or less) by between 1.7% and 2.6%. This represents a significant boost in real wages, especially considering that the real wage growth of this group during the 2000-2019 period was actually negative, between -5% to -6% .[17] Second, in spite of the large inflow of college-educated immigrants, the com-

[16] Tables 14 and 15 in Appendix A report the wage effects on foreign-born.

[17] See Table 11.

plementarity between immigrants and natives, especially when capturing using the specific complementarity within college educated (columns (2) to (4)), attenuated or reversed most of the competition effect for the groups with some college education or a college degree. As a result, they also experienced between no and small effects (between -0.5% and +0.7%), mostly not statistically significant if we account for the simulated standard errors. Third, the average effect on wages of natives was small, overall positive (+0.5% to +0.8%) and not statistically significant, when accounting for the simulated standard errors. Let us emphasize that, relative to the estimated impact of the immigration flows during the 1990s and early 2000s calculated in Ottaviano and Peri (2012), the effects we find here are more favorable to less educated Americans (now gaining about 2%, versus 0 to 1% as found in that previous analysis from Ottaviano and Peri (2012)) and are similar for college graduate (having close to 0 effects).

Columns (5) and (6) of Table 9 show the effects of immigration on native employment-population ratios, calculated by simply multiplying the cell-specific percentage change in immigrant employment, approximated by the difference of log immigrant employment, between 2000 and 2019, times the β_{emp} estimates from Table 7 for the corresponding education group. We show two versions of those effects. In column (5) we use the set of four education-specific estimates for the sample of all workers (column (2) in Panel B of Table 7), while in column (6) we use the larger estimates for the sample of full-time workers only (column (4) in Panel B of Table 7). We then aggregate results by education group and overall, weighting by cell native employment at the beginning of the interval of interest (i.e., 2000 for Table 9).

These simulated values reveal two additional potential effects of immigration. First, during the 2000-2019 period, immigration boosted the employment-population ratio of natives on average by 2.4 percentage points (and as much as 7.4 p.p. when considering full-time workers). This employment effect suggests that the wage complementarity and the occupational upgrading pulled more natives into employment. Second, the effect is particularly strong and positive for highly educated natives, whose employment-population ratio increased by 4.2 p.p. (possibly up to 12.4 p.p. for full-time workers). The group of least educated saw a decrease in employment-population ratio, in spite of the positive coefficient estimated in Table 7. This is because the least educated group experienced a decline in the supply of immigrants over the 2000-2019 period. Estimates in column (5) suggest that groups of native workers with high school degrees, some college education and college degree, all experienced an increase (between 2 and 4.2 p. p.) in their employment-population ratio due to immigration.

Let us acknowledge that the calculated effects on the employment-population ratio of natives are much more basic than those for wages. They only account for the direct partial effect of immigrants on this measure of labor supply of natives in each cell. The wage effects, on the other hand, account for complementarity across skill cells as generated by the model in Section 2. Still, these simulations confirm that at the national level, immigration results in zero to positive wage effects and predominantly positive employment effects for natives. Neither predominant wage competition nor crowding out of natives from the labor market seem consistent with these results. These set of results are instead consistent with a significant degree of complementarity between immigrants and natives.

Table 10 shows the same simulated effects and specifications as Table 9, but, in this case, in response to changes in immigrant flows between 2019 and 2022. While there is some evidence that the US is experiencing a resurgence of immigrants during the post-Covid years, the period we consider, which includes the pandemic years, represents a period of particularly low average inflows and especially among immigrants with low schooling. Hence, the simulated wage effects are very small for native workers, but still positive for less educated ones with increases up to 1.1%, and negligible effects for college-educated natives. Similarly, the simulated effects on the employment-population ratio are very small, with values reaching at most a 1.4 percentage point increase for college-educated natives when using the largest parameter estimates. Therefore, even using the most current and up to date national data on immigration and our updated estimates, the positive wage and employment effect on natives, while small, still apply.

Table 9: Calculated effect on native wages and employment-population ratio, as response to change in immigrant labor supply 2000-2019

	Percentage change in native wages				Percentage change in native supply	
	(1)	(2)	(3)	(4)	(5)	(6)
Group:						
No High School Degree	1.8	1.8	2.4	1.7	-1.5	-6.1
	(0.9)	(0.9)	(1.0)	(0.8)		
High School Degree	2.1	2.0	2.6	2.1	2.8	9.0
	(0.3)	(0.3)	(0.6)	(0.3)		
Some College Education	0.5	0.7	0.4	-0.2	2.0	6.0
	(0.5)	(0.5)	(0.5)	(0.2)		
College Degree	-0.5	0.1	-0.1	0.7	4.2	12.4
	(0.5)	(0.4)	(0.4)	(0.2)		
Average	0.5	0.8	0.8	0.8	2.4	7.4
	(0.5)	(0.4)	(0.5)	(0.3)		
Parameter configuration:						
$1/\sigma_{H-L}$	0.54	0.54	0.71	0.54		
	(0.06)	(0.06)	(0.15)	(0.06)		
$1/\sigma_{EDU,H}$	0.16	0.16	0.16	0		
	(0.08)	(0.08)	(0.08)			
$1/\sigma_{EDU,L}$	0.03	0.03	0.03	0		
	(0.02)	(0.02)	(0.02)			
$1/\sigma_{EXP}$	0.16	0.16	0.16	0.16		
	(0.05)	(0.05)	(0.05)	(0.05)		
$1/(\sigma_N)_H$	0.058	0.10	0.10	0.10		
	(0.025)	(0.008)	(0.008)	(0.008)		
$1/(\sigma_N)_L$	0.058	0.045	0.045	0.045		
	(0.025)	(0.018)	(0.018)	(0.018)		

Notes: Percentage wage changes for each education group are obtained averaging the wage change of each education-experience group weighting by the wage share in the education group. The wage change for each group is calculated using formula (16) from Appendix C. Since the parameters used are normally distributed random variables we proceed as follows. We first generate 1,000 extractions for a given configuration of the parameters from a joint normal distribution. We then calculate the wage effect for each education-experience group and then we take the average and the standard deviation of the 1,000 values. The average changes and their standard errors are obtained by weighting changes (and standard errors) of each education group by its share in the 2019 wage bill of the group. Columns (1) to (4) report percentage changes in native wages each using a different configuration of mean and standard deviation for the distribution of parameters of interest. Simulated standard errors are reported in parentheses. Columns (5) and (6) report percentage changes in native employment-to-population ratios obtained with a partial effect approach. We employ cell-specific percentage changes in immigrant employment and the coefficients estimated in column (2) and column (4) of Table 7, respectively, to compute the effect on native supply. Education group effects and average effects are obtained using native employment at the beginning of the period as weight.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

Table 10: Calculated effect on native wages and employment-population ratio, as response to change in immigrant labor supply 2019-2022

	Percentage change in native wages				Percentage change in native supply	
	(1)	(2)	(3)	(4)	(5)	(6)
Group:						
No High School Degree	0.8	0.8	1.1	0.7	-0.1	-0.3
	(0.3)	(0.3)	(0.3)	(0.3)		
High School Degree	0.9	0.9	1.1	0.9	0.0	0.1
	(0.1)	(0.1)	(0.3)	(0.1)		
Some College Education	-0.0	-0.0	-0.1	-0.3	-0.2	-0.6
	(0.1)	(0.1)	(0.1)	(0.0)		
College Degree	-0.2	-0.1	-0.2	-0.0	0.5	1.4
	(0.1)	(0.1)	(0.1)	(0.0)		
Average	0.0	0.1	0.1	0.1	0.1	0.4
	(0.1)	(0.1)	(0.1)	(0.1)		
Parameter configuration:						
$1/\sigma_{H-L}$	0.54	0.54	0.71	0.54		
	(0.06)	(0.06)	(0.15)	(0.06)		
$1/\sigma_{EDU,H}$	0.16	0.16	0.16	0		
	(0.08)	(0.08)	(0.08)			
$1/\sigma_{EDU,L}$	0.03	0.03	0.03	0		
	(0.02)	(0.02)	(0.02)			
$1/\sigma_{EXP}$	0.16	0.16	0.16	0.16		
	(0.05)	(0.05)	(0.05)	(0.05)		
$1/(\sigma_N)_H$	0.058	0.10	0.10	0.10		
	(0.025)	(0.008)	(0.008)	(0.008)		
$1/(\sigma_N)_L$	0.058	0.045	0.045	0.045		
	(0.025)	(0.018)	(0.018)	(0.018)		

Notes: Percentage wage changes for each education group are obtained averaging the wage change of each education-experience group weighting by the wage share in the education group. The wage change for each group is calculated using the formula (16) from Appendix C. Since the parameters used are normally distributed random variables we proceed as follows. We first generate 1,000 extractions for a given configuration of the parameters from a joint normal distribution. We then calculate the wage effect for each education-experience group and then we take the average and the standard deviation of the 1,000 values. The average changes and their standard errors are obtained by weighting changes (and standard errors) of each education group by its share in the 2019 wage bill of the group. Columns (1) to (4) report percentage changes in native wages each using a different configuration of mean and standard deviation for the distribution of parameters of interest. Simulated standard errors are reported in parentheses. Columns (5) and (6) report percentage changes in native employment-population ratios obtained with a partial effect approach. We employ cell-specific percentage changes in immigrant employment and the coefficients estimated in column (2) and column (4) of Table 7, respectively, to compute the effect on native supply. Education group effects and average effects are obtained using native employment at the beginning of the period as weight.
Source: ACS data downloaded from IPUMS on 01/12/2024.

7 Conclusions

In this paper we have extended and updated a framework that has been broadly used since the 2000s-2010s, to enrich and update our understanding of the recent national effects of immigration on US wages, employment and labor markets. This framework, led by similar work by Borjas (2003), Ottaviano and Peri (2012), and Manacorda et al. (2012), has had a profound influence on policy discussions. By differentiating the impact of immigrants on the wages of natives across skill groups, this model allows one to measure the national wage effects of immigration while accounting for both competition and complementarity across skill groups.

In this present paper we update the estimates of the key parameters that capture productive complementarity between natives and immigrants and across skill groups by using more recent data and by applying a modern set of rigorous econometric techniques. Additionally, relative to the approach of the 2010s, we explicitly acknowledge that native employment, not just wages, can respond to immigration. We are the first to use then this framework to estimate the effect of immigration on the employment-population ratio of natives.

Our estimates establish that immigrants have a substantial degree of productive complementarity with natives. This offsets the competition effect, resulting in a boost of native wages and in an increase of natives' employment-population ratio in response to inflows for most native workers. We also show that after the year 2000, inflows of immigrants became more concentrated among college educated compared to the past, and that their complementarity with skilled natives was large enough not to harm, but rather to boost the wages of less educated American workers. Additionally, we find that one possible mechanism through which immigration results in a positive complementarity and a wage boost for natives is through positive occupational responses among natives. This is consistent with specialization between natives and immigrants along the lines of comparative advantage, so that an increase in immigration prompts natives to upgrade and specialize in terms of occupations.

Finally, our simulations of wage and employment effects of immigrants in the 20 years up to 2020 and in the last four years for which we have data (2019-2022), based on the updated, better and more carefully estimated coefficients, show a clear positive/complementary effect of immigrants on wages of less educated natives without suggesting employment displacement (i.e., immigrants taking the jobs) of most native workers. This paper, by focusing national effects as compared to the many recent papers considering local effects, provides a complementary and important picture of immigrants in the US labor markets.

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Appendix A Summary statistics and additional evidence

Table 11: Immigration and changes in native wages by education-experience groups, 2000–2019

Education (1)	Experience (2)	2000-2019 percentage change in hours worked due to new immigrants (%) (3)	2000-2019 percentage change in native weekly wages (%) (4)
No High School Degree	1 to 5 years	-18.4	-11.0
	6 to 10 years	-28.0	-6.0
	11 to 15 years	-18.6	-7.3
	16 to 20 years	-6.3	-7.8
	21 to 25 years	4.8	-4.5
	26 to 30 years	13.0	-6.8
	31 to 35 years	23.7	-5.8
	36 to 40 years	28.4	-6.4
	All Experience Groups	-1.7	-5.6
High School Degree	1 to 5 years	0.4	-12.5
	6 to 10 years	2.5	-11.1
	11 to 15 years	4.0	-9.8
	16 to 20 years	5.4	-4.1
	21 to 25 years	6.9	-4.1
	26 to 30 years	11.0	-2.2
	31 to 35 years	13.9	-0.7
	36 to 40 years	16.3	-1.7
	All Experience Groups	7.2	-6.9
Low Education	**All Experience Groups**	4.5	-5.3
Some College Education	1 to 5 years	1.4	-12.5
	6 to 10 years	1.1	-13.1
	11 to 15 years	1.3	-10.3
	16 to 20 years	1.5	-7.5
	21 to 25 years	3.4	-4.9
	26 to 30 years	6.3	-2.9
	31 to 35 years	10.4	-4.5
	36 to 40 years	17.1	-4.8
	All Experience Groups	4.0	-7.5
College Degree	1 to 5 years	6.6	-4.7
	6 to 10 years	9.9	-3.8
	11 to 15 years	11.9	-5.0
	16 to 20 years	12.8	-2.5
	21 to 25 years	13.5	3.4
	26 to 30 years	12.4	6.2
	31 to 35 years	20.6	5.4
	36 to 40 years	30.4	3.4
	All Experience Groups	13.0	-0.3
High Education	**All Experience Groups**	8.4	1.8

Notes: This table extends Ottaviano and Peri (2012)'s Table 1 to the 2000-2019 period. For the 32 education-experience cells the table reports the percentage change, between 2000 and 2019, of hours worked due to hours worked by immigrants, and the percentage change in real weekly wages for natives (in 1999 US dollars). Averages of native weekly wages across groups are weighted by hours worked by natives.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

Table 12: Estimates of $\frac{1}{\sigma_{IMMI}}$, by education group - Other samples

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
	Panel A: 1960-2019			
Women, Rel. hours (IV) - No HS diploma	0.056***	0.059***	0.053***	0.058***
	(0.010)	(0.007)	(0.011)	(0.008)
Women, Rel. hours (IV) - HS diploma	0.021**	0.027***	0.025***	0.034***
	(0.009)	(0.007)	(0.010)	(0.006)
Women, Rel. hours (IV) - Some college	0.028***	0.036***	0.037***	0.046***
	(0.011)	(0.008)	(0.011)	(0.007)
Women, Rel. hours (IV) - College degree	0.031***	0.023***	0.048***	0.043***
	(0.012)	(0.009)	(0.012)	(0.007)
Pooled, Rel. hours (IV) - No HS diploma	0.042***	0.045***	0.044***	0.050***
	(0.010)	(0.007)	(0.012)	(0.008)
Pooled, Rel. hours (IV) - HS diploma	0.014	0.023***	0.020*	0.032***
	(0.010)	(0.007)	(0.011)	(0.006)
Pooled, Rel. hours (IV) - Some college	0.019*	0.029***	0.028**	0.040***
	(0.011)	(0.008)	(0.012)	(0.007)
Pooled, Rel. hours (IV) - College degree	0.047***	0.039***	0.061***	0.052***
	(0.013)	(0.009)	(0.013)	(0.007)
	Panel B: 2000-2019			
Women, Rel. hours (IV) - No HS diploma	0.155***	0.129***	0.067**	0.083***
	(0.032)	(0.028)	(0.029)	(0.018)
Women, Rel. hours (IV) - HS diploma	0.029***	0.028***	0.029***	0.033***
	(0.006)	(0.005)	(0.007)	(0.005)
Women, Rel. hours (IV) - Some college	0.048***	0.048***	0.053***	0.057***
	(0.006)	(0.004)	(0.007)	(0.004)
Women, Rel. hours (IV) - College degree	0.079***	0.076***	0.090***	0.091***
	(0.007)	(0.005)	(0.009)	(0.006)
Pooled, Rel. hours (IV) - No HS diploma	0.148***	0.134***	0.044	0.077***
	(0.039)	(0.034)	(0.034)	(0.023)
Pooled, Rel. hours (IV) - HS diploma	0.016**	0.017***	0.017**	0.023***
	(0.007)	(0.005)	(0.007)	(0.004)
Pooled, Rel. hours (IV) - Some college	0.036***	0.039***	0.041***	0.047***
	(0.006)	(0.005)	(0.007)	(0.004)
Pooled, Rel. hours (IV) - College degree	0.097***	0.094***	0.105***	0.107***
	(0.008)	(0.005)	(0.009)	(0.006)
Weights	Yes	No	Yes	No
Experience FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No

Notes: In each panel, the set of 4 column-specific coefficients reported from rows (1) to (4) pertains to the same regression, where (log) relative weekly wage for women is the outcome variable. The set of four column-specific coefficients reported from rows (5) to (8) pertains to the same regression, where pooled (log) relative weekly wage is the outcome instead. Coefficients are 2SLS estimates on the interaction of (log) relative hours worked with 4 education dummies (no high school diploma, high school diploma, some college education, college degree or more), where (log) relative hours are instrumented by (log) relative population. Cell employment is used as weight. Robust standard errors are clustered at the cell level (education by experience).
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

Table 13: Effect on native employment-to-population ratio - OLS estimates

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
	Panel A: 1960-2019			
Men, Rel. population	-0.045***	-0.043***	-0.051***	-0.046***
	(0.011)	(0.014)	(0.011)	(0.013)
Women, Rel. population	-0.050***	-0.036*	-0.061***	-0.052***
	(0.014)	(0.019)	(0.017)	(0.019)
Pooled, Rel. population	-0.041***	-0.035**	-0.045***	-0.041***
	(0.012)	(0.014)	(0.012)	(0.013)
Men, Rel. population (fixing native)	0.070***	0.078***	0.072***	0.072***
	(0.007)	(0.007)	(0.007)	(0.008)
Women, Rel. population (fixing native)	0.078***	0.079***	0.112***	0.108***
	(0.011)	(0.013)	(0.012)	(0.013)
Pooled, Rel. population (fixing native)	0.060***	0.060***	0.064***	0.061***
	(0.011)	(0.011)	(0.008)	(0.007)
	Panel B: 2000-2019			
Men, Rel. population	0.018	0.024	0.009	0.011
	(0.017)	(0.017)	(0.018)	(0.015)
Women, Rel. population	-0.009	-0.006	-0.009	-0.007
	(0.018)	(0.019)	(0.024)	(0.017)
Pooled, Rel. population	0.007	0.012	0.002	0.005
	(0.017)	(0.017)	(0.018)	(0.014)
Men, Rel. population (fixing native)	0.053***	0.053***	0.065***	0.053***
	(0.010)	(0.008)	(0.012)	(0.015)
Women, Rel. population (fixing native)	0.049***	0.046***	0.064***	0.047***
	(0.010)	(0.013)	(0.016)	(0.017)
Pooled, Rel. population (fixing native)	0.049***	0.049***	0.058***	0.048***
	(0.009)	(0.009)	(0.010)	(0.012)
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Each coefficient of the table represents a different OLS regression, where the outcome variable is represented by the ratio between native employment and native population (men, women, or pooled, depending on the row). In each panel, rows (1) to (3) report the OLS coefficient on (log) relative population. In rows (4) to (6), the OLS coefficient on the same explanatory variable built by fixing native population to the first year of the period considered (i.e. 1960 for Panel A, 2000 for Panel B) is reported. Such modification is not applied to the outcome variable. Cell employment is used as weight. Robust standard errors are clustered at the cell level (education by experience).
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

Table 14: Calculated long-run effects of immigration on foreign-born, 2000–2019

	Percentage change in foreign-born wages			
	(1)	(2)	(3)	(4)
Group:				
No High School Degree	2.1	2.2	2.7	2.0
	(1.1)	(1.0)	(1.1)	(1.0)
High School Degree	-2.6	-1.7	-1.2	-1.7
	(1.9)	(1.5)	(1.5)	(1.5)
Some College Education	-2.4	-4.5	-4.7	-5.4
	(1.4)	(0.7)	(0.7)	(0.4)
College Degree	-6.7	-10.8	-10.9	-10.1
	(2.5)	(0.9)	(0.9)	(0.8)
Average	-3.5	-5.7	-5.6	-5.6
	(1.9)	(1.0)	(1.0)	(0.9)
Parameter configuration:				
$1/\sigma_{H-L}$	0.71	0.71	0.54	0.71
	(0.15)	(0.15)	(0.06)	(0.15)
$1/\sigma_{EDU,H}$	0	0	0	0.3
				(0.11)
$1/\sigma_{EDU,L}$	0	0	0	0.3
				(0.11)
$1/\sigma_{EXP}$	0.16	0.16	0.16	0.16
	(0.05)	(0.05)	(0.05)	(0.05)
$1/(\sigma_N)_H$	0.058	0.1	0.1	0.1
	(0.025)	(0.008)	(0.008)	(0.008)
$1/(\sigma_N)_L$	0.058	0.03	0.03	0.03
	(0.025)	(0.006)	(0.006)	(0.006)

Notes: This table reports the simulated wage effects on foreign-born workers. The procedure used to build this table is the same as the one described for the simulations of the impact of immigration on natives, outlined in Section 6.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

Table 15: Calculated long-run effects of immigration on foreign-born, 2019–2022

	Percentage change in foreign-born wages			
	(1)	(2)	(3)	(4)
Group:				
No High School Degree	1.2	1.1	1.4	1.1
	(0.3)	(0.2)	(0.3)	(0.2)
High School Degree	1.0	1.0	1.3	1.0
	(0.2)	(0.1)	(0.3)	(0.1)
Some College Education	0.2	0.3	0.2	0.1
	(0.2)	(0.1)	(0.1)	(0.0)
College Degree	-0.7	-1.1	-1.1	-1.0
	(0.2)	(0.1)	(0.1)	(0.1)
Average	-0.2	-0.3	-0.3	-0.3
	(0.2)	(0.1)	(0.2)	(0.1)
Parameter configuration:				
$1/\sigma_{H-L}$	0.71	0.71	0.54	0.71
	(0.15)	(0.15)	(0.06)	(0.15)
$1/\sigma_{EDU,H}$	0	0	0	0.3
				(0.11)
$1/\sigma_{EDU,L}$	0	0	0	0.3
				(0.11)
$1/\sigma_{EXP}$	0.16	0.16	0.16	0.16
	(0.05)	(0.05)	(0.05)	(0.05)
$1/(\sigma_N)_H$	0.058	0.1	0.1	0.1
	(0.025)	(0.008)	(0.008)	(0.008)
$1/(\sigma_N)_L$	0.058	0.03	0.03	0.03
	(0.025)	(0.006)	(0.006)	(0.006)

Notes: This table reports the simulated wage effects on foreign-born workers. The procedure used to build this table is the same as the one described for the simulations of the impact of immigration on natives, outlined in Section 6.
Source: ACS data downloaded from IPUMS on 01/12/2024.

Appendix B IV descriptives and tests

Table 16: Top-10 countries of origin by 1960-1980 increase in nationals residing in the US

1960		1980		1980-1960	
Country (1)	Headcount (2)	Country (3)	Headcount (4)	Country (5)	Difference (4)-(2)
Italy	1,191,299	Mexico	1,719,940	Mexico	1,255,283
Canada	860,851	Italy	783,920	Abroad, N.S.	607,125
Germany	844,438	Germany	763,400	Cuba	493,779
Poland	707,831	Canada	757,000	Philippines	337,107
UK	665,240	Abroad, N.S.	658,120	China	291,852
Russia/Other URSS	655,854	UK	578,420	Korea	196,217
Mexico	464,657	Cuba	555,840	India	182,678
Ireland	308,815	Philippines	419,500	Jamaica	138,203
Austria	274,463	Poland	398,260	Dominican Republic	129,203
Hungary	226,077	China	379,300	Colombia	111,865

Notes: For consistency, foreign-born individuals younger than 18 years of age are dropped from the count. We aggregate some countries together in 1980 in order to be more consistent with the lower level of detail present in the 1960 breakdown of origins. This implies, for instance, that China includes Hong Kong, Macau, Mongolia and Taiwan; Korea includes North and South Korea; India includes Bangladesh, Bhutan, Myanmar and Sri Lanka.
Source: Decennial Census data downloaded from IPUMS on 01/12/2024.

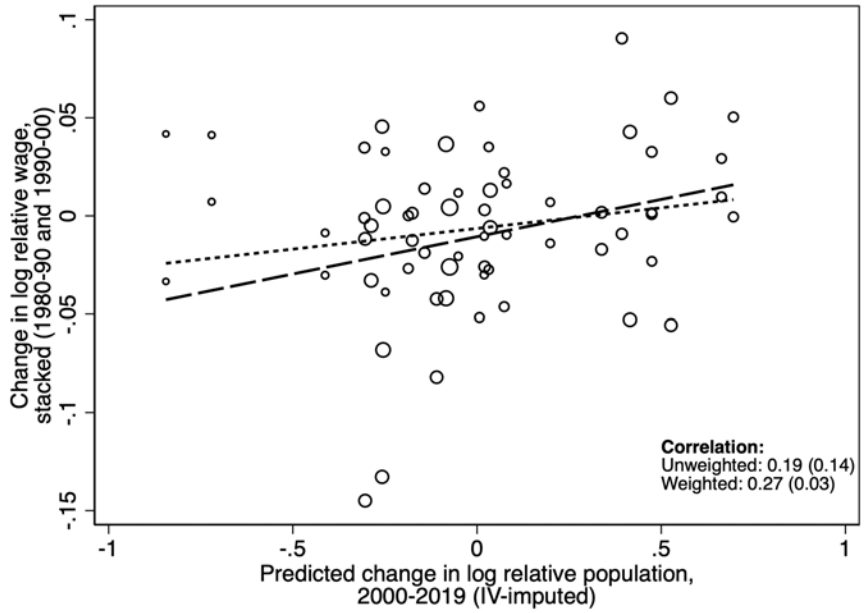
Table 17: Net flows for selected shares

Country	1960 (2)	1980 (3)	Difference (4)
Mexico	331,572	1,446,600	1,115,028
Cuba	55,886	401,140	345,254
China	71,412	297,440	226,028
Philippines	65,747	332,900	267,153
Korea	4,284	179,080	174,796
North America	550,459	435,260	-115,199
Central America	106,912	689,960	583,048
South America	55,281	398,800	343,519
Europe	2,870,343	2,474,860	-395,483
Africa	15,443	134,300	118,857
Asia	131,160	839,260	708,100
Oceania	19,519	52,540	33,021

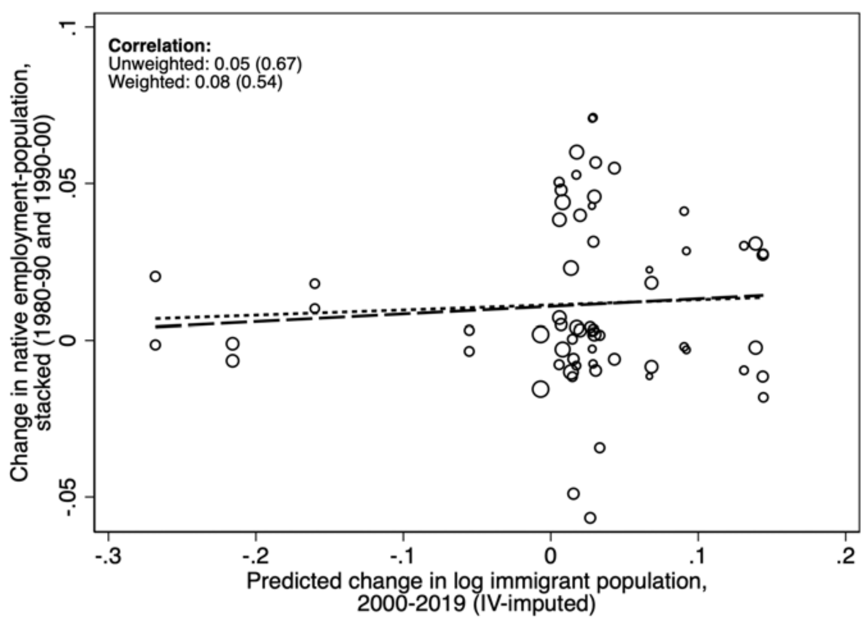
Notes: For consistency, foreign-born individuals younger than 18 years of age are dropped from the count. We aggregate some countries together in 1980 in order to be more consistent with the lower level of detail present in the 1960 breakdown of origins. This implies, for instance, that China includes Hong Kong, Macau, Mongolia and Taiwan; Korea includes North and South Korea. The discrepancy of some values with those in Table 16 is due to the exclusion from the sample of individuals who are predicted to have more than 40 years of experience in the labor market (this restriction is imposed when building the experience cells throughout the paper).
Source: Decennial Census data downloaded from IPUMS on 01/12/2024.

Figure 7: Pre-trends in outcomes without fixed effects

(a) Relative wage



(b) Native employment-population ratio



Notes: This figure plots the correlation between changes in outcomes of interest before 2000 and changes in corresponding IV measures after 2000 by skill cell, without controlling for education nor decade. The upper (lower) panel displays 1980-1990 and 1990-2000 stacked changes in log relative wage (native employment-population ratio) and IV-imputed changes for 2000-2019 in log relative population (log immigrant population) by skill cell. Circle sizes are proportional to 1980 cell employment (used as weight). Correlation coefficients (and corresponding significance values) are reported. The dotted line represents an OLS unweighted regression of changes in outcome on changes in IV measures, while the long-dashed line represents the same OLS regression with weights.

Table 18: 2SLS estimates of breakdown by education - Tests

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Elasticity estimates (2000-2019)				
Pooled, Rel. employment by education 1				
Shea's Partial R^2	0.46	0.53	0.33	0.43
First-stage F	3.41	5.45	4.94	7.87
Sanderson-Windmeijer corrected F	28.64	53.43	13.61	28.57
Pooled, Rel. employment by education 2				
Shea's Partial R^2	0.67	0.81	0.71	0.83
First-stage F	695.67	753.20	1719.18	1271.23
Sanderson-Windmeijer corrected F	98.83	338.47	91.77	359.50
Pooled, Rel. employment by education 3				
Shea's Partial R^2	0.67	0.81	0.71	0.83
First-stage F	344.85	386.86	351.99	358.60
Sanderson-Windmeijer corrected F	140.45	445.89	133.17	320.72
Pooled, Rel. employment by education 4				
Shea's Partial R^2	0.65	0.80	0.68	0.81
First-stage F	303.58	351.50	277.14	218.04
Sanderson-Windmeijer corrected F	103.99	252.29	81.07	159.96
Kleibergen-Paap stat.	3.78	5.67	3.35	6.65
Panel B: Labor supply estimates (2000-2019)				
Pooled, Imm. employment by education 1				
Shea's Partial R^2	0.16	0.23	0.14	0.22
First-stage F	3.41	8235.22	5841.87	5044.74
Sanderson-Windmeijer corrected F	60.81	57.14	53.93	57.50
Pooled, Imm. employment by education 2				
Shea's Partial R^2	0.16	0.23	0.14	0.22
First-stage F	30629.73	22705.31	17244.44	11120.29
Sanderson-Windmeijer corrected F	59.97	56.05	53.44	56.47
Pooled, Imm. employment by education 3				
Shea's Partial R^2	0.16	0.23	0.14	0.22
First-stage F	5499.51	5657.80	4261.85	4196.84
Sanderson-Windmeijer corrected F	59.14	54.45	52.45	54.82
Pooled, Imm. employment by education 4				
Shea's Partial R^2	0.16	0.23	0.14	0.22
First-stage F	6500.43	6787.29	6170.56	4862.12
Sanderson-Windmeijer corrected F	59.53	55.93	52.96	55.77
Kleibergen-Paap stat.	11.12	9.44	10.33	8.42

Notes: This table reports validity tests for the 2SLS regressions with multiple endogenous variables and instruments of Table 7. The same structure of Table 7 is maintained, so that each test or statistic reported here refers to the coefficient in the same position (and specification) of Table 7.

Appendix C Formula for the wage effect of all immigrants on native wages

Let us denote the change in foreign-born supply between two periods in education k-experience j group as ΔL_{Fkj}, and the initial value of supply of immigrants in that group as L_{Fkj}. We then use the demand function for domestic workers of skill $\{k, j\}$, obtained by equating the marginal product of that skill group (derived from production function (1)-(6)) to their wages and take a total (log) differential of that demand function with respect to (log) changes in the supply of each group of foreign-born. The resulting expression, capturing the total percentage change in native wage w_{Dkj}, is as follows:

$$\begin{aligned}
\left(\frac{\Delta w_{Dkj}}{w_{Dkj}}\right)^{Total} = \; & \frac{1}{\sigma_{HL}} \sum_{H,L} \sum_{l} \sum_{i} \left(s_{Fli} \frac{\Delta L_{Fli}}{L_{Fli}} \right) \\
& + \left(\frac{1}{\sigma_l} - \frac{1}{\sigma_{HL}} \right) \sum_{l} \sum_{i} \left(s_{Fli}^{HH,LL} \frac{\Delta L_{Fli}}{L_{Fli}} \right) \\
& + \left(\frac{1}{\sigma_{EXP}} - \frac{1}{\sigma_k} \right) \sum_{i} \left(s_{Fki}^{k} \frac{\Delta L_{Fki}}{L_{Fki}} \right) \\
& + \left(\frac{1}{\sigma_N} - \frac{1}{\sigma_{EXP}} \right) \left(s_{Fkj}^{kj} \frac{\Delta L_{Fkj}}{L_{Fkj}} \right)
\end{aligned} \tag{16}$$

In equation (16) the terms s_{Fkj} represent the share of wages going to foreign-born workers F of education k and experience j, within the group defined by the superscript. Hence, for instance, s_{Fkj}^{kj} is the share of that group within income accruing to all workers of education k and experience j, while s_{Fkj}^{k} is the share within workers of education k, and s_{Fkj} is the share among all workers. The running indicator i denotes different experience groups and l different education groups within H and L, where H, L are the broadest aggregates of workers with high school diploma or less and with some college education or more. Equation (16) is the formula we use in Section 6 to obtain the total wage effects of immigration for each group of native workers.