Immigration's Effect on US Wages and Employment Redux*

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Abstract

This article revives and enhances the factor-supply approach to estimate the effects of changes in immigrant supply on wages and employment of US natives. We introduce and validate a skill-based shift-share IV for immigrants' labor supply. We find a positive impact of immigration on natives' employment and a significant elasticity of complementarity between natives and immigrants. Consistent with these estimates, we find significant task complementarity and occupational upgrading of native workers in response to immigrants. Finally, we calculate that immigration over 2000-2023 increased wages of non-college-educated natives by 2.6 to 3.4%, with small effects on other groups.

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1 Introduction and Review of the Literature

A classic question in economics, one that remains at the center of the political debate as the US labor force shrinks while immigration reforms remain unpopular, is: *what is the impact of immigrants on wages and employment of US workers?* Influential papers in the 2010s, particularly Ottaviano and Peri (2012) and Manacorda, Manning, and Wadsworth (2012) – which extended and complemented predecessor papers such as Borjas (2003) and Borjas and Katz (2007a) – developed a systematic approach to estimate key aggregate parameters for calculating immigration's effects on national wages of US (or UK) workers with different education and experience levels. This is known as the "factor-supply" approach.

These studies treated immigration as a change to the national supply of a set of labor market skills and examined long-run effects on native wages, accounting for both competition and complementarity between native and immigrant workers by employing a nested constant elasticity of substitution (CES) production function with skill cells as labor inputs. This framework provides a reasonable approximation of US labor markets in the long run, when workers' wages equal their marginal productivity, their mobility arbitrages away local differences, and the degree of competition versus complementarity depends on skill differences. These influential papers have been cited extensively and have provided benchmark policy calculations for assessing the effects of immigrants on US wages in the 1990s and early 2000s.

However, while influential, this approach has not been updated to estimate the impact of more recent immigrant flows (post-2000) or modernized using current econometric techniques for estimating key parameter values. Nor has it been augmented to incorporate the long-run effects of immigration on native labor supply – which the earlier models assumed to be unresponsive to immigrants – or to investigate occupational and task specialization as important channels creating imperfect labor market competition between natives and immigrants. Understanding task specialization could help explain both the complementarity and labor supply responses of natives.

This paper builds on the insights of those seminal studies by introducing a more rigorous identification approach and extending the analysis to include effects on native employment and occupational specialization outcomes, providing a comprehensive picture of immigration's impact on national labor markets for US natives. Additionally, we update the analysis to consider new immigration trends by focusing on the 2000-2023 period. Since 2000, immigration flows have changed significantly, becoming smaller and more concentrated among college-educated individuals relative to the 1980-2000 period studied by the previous set of papers (Ottaviano and Peri (2012), Manacorda et al. (2012),Borjas (2003), and Borjas and Katz (2007b)), when substantial net inflows of less-educated immigrants were occurring.

Before discussing our innovations, it is useful to review the three approaches most commonly used to estimate the effects of immigration on labor market outcomes, highlighting their strengths and weaknesses while positioning our contribution within this literature. We will mainly review studies analyzing the US labor markets.[1]

A first line of research stresses credible causal identification through the use of "natural experiments" by identifying exogenous, sudden, and significant changes in immigrant supply to specific US locations. This approach compares native wages, employment, and other labor market outcomes in locations where sudden immigration changes occurred ("treated" area) to locations where they did not ("control" areas). Famous studies using this approach include the seminal paper by Card (1990) studying the large inflow of Cubans to Miami in 1981 (the *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 analyzed the sudden migration flow from Puerto Rico to Orlando after Hurricane Maria, and Kugler and Yuksel (2011), which examined the consequences of the inflow of Central Americans after Hurricane Mitch.[2] While this approach may bring us closer to causally identifying the average impact of sudden immigration events, the specific characteristics of these events, including their suddenness, the particular locations, and the skill composition of immigrant groups, differ substantially from typical US immigration patterns. This raises questions about the external validity of these results. Extrapolating these average local estimates for specific cities into

[1]Chapter 5 of National Academies of Sciences and Medicine (2017) is probably the most well-known review of these studies and covers a large body of research.

[2]Applications of this approach to immigration episodes in other countries are numerous; many are summarized in Tumen (2015).

national effects from continued, slower, geographically dispersed, and more predictable immigration flows with different skill distributions is challenging.

A second approach better addresses external validity concerns by exploiting changes in immigration inflows *across all US commuting zones* – which approximate local labor markets – driven by increases and decreases in flows from specific countries of origin. These flows are distributed as differential "shocks" across US commuting zones proportionally to preexisting immigrant networks, which are known to affect the location choices of new arrivals. Several papers have used this approach, known as "shift-share" instrumental variables, to compare labor market outcomes across US commuting zones (Card (2001, 2009); Peri and Sparber (2009); Peri, Shih, and Sparber (2015); Monras (2020a)). Due to its broad applicability, recent methodological developments have provided stringent tests for identification validity in this context that have increased its credibility (Goldsmith-Pinkham, Sorkin, and Swift (2020)).

Both of these approaches belong to the "local area approach" as they use variations in migration and outcomes across US geographical areas. Recently, this literature has been revived and has explored departures from the classical labor market framework by considering firms' monopsony power, which is more relevant at the local than at the national level. These local monopsony models produce negative wage effects of immigration, as higher immigrant supply, especially of less-educated and undocumented workers, increases firms' bargaining power (Amior and Manning (2020); Amior (2020)). Additionally, related studies have examined how local (state-level) institutions may affect the impact of immigration on wages. For instance, Edo and Rapoport (2019) show how minimum wages can attenuate the wage effects and exacerbate local employment effects of immigrant inflows.[3]

While important, the local area literature described above and the recent contributions focusing on the monopsony power of firms have several limitations. In particular, they are only partially useful for understanding the national effects of recent (post-2000) im-

[3]The recent literature analyzing the impact of local immigration shock (mostly outside of the US) has gone beyond local area data and has taken advantage of individual longitudinal data to follow the impact of immigration on individual native outcomes (see, e.g., Foged and Peri (2016) and Dustmann, Schönberg, and Stuhler (2017)). While this is a very important evolution, evaluating aggregate effects on skill groups remains a central question in this literature.

migration to the US for several reasons. First, internal mobility responses of natives across commuting zones to immigration inflows can be large (Borjas (2001); Basso and Peri (2020); Dustmann et al. (2017)), generating effects that spill over beyond the initial labor market. Hence, inferring national market effects from local ones requires additional assumptions to model these spillovers (Amior (2020)) or risks being misleading. Additionally, labor mobility can reduce the local monopsony power of firms, and therefore, in the longer run and in the aggregate economy, the bargaining power of workers can be larger than what is assumed in those models. A second limitation is that focusing on immigrants' impact across areas has led this approach to oversimplify the analysis of skill composition, often treating immigrants and natives as only one type of undifferentiated labor (e.g., Amior and Manning (2020); Amior (2020)). Finally, and most importantly, focusing on monopsony effects or the role of minimum wages is more relevant when immigration consists of less-educated immigrants. This scenario better describes US immigration in the 1990s than it does in the post-2000 period, when the number of less-skilled immigrants remained stable or decreased while college-educated immigrants grew significantly.[4] To understand the national effects of long-run inflows of intermediate- to high-skilled immigrant workers in the US labor market, a competitive labor demand and supply model with careful analysis of skill differences and competition/complementarities seems more insightful than one focusing on local monopsony power and undifferentiated labor.

Hence, complementing these two lines of inquiry but focusing on skills and on US national labor markets, we revive and expand a third approach pioneered by Borjas (2003), Borjas and Katz (2007a), Ottaviano and Peri (2012), and Manacorda et al. (2012). We refer to this as the national "factor-supply" approach, which analyzes the national effects of immigration on the wages of native workers across different skill groups.

This framework provides insights and tools to analyze the national labor market effects of immigration by workers' skills that the other two approaches, focused on identification and average local effects, do not offer. By separating the US into distinct labor markets by skills (proxied by education and experience groups), this approach internalizes geo-

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

graphical mobility responses of individuals, reduces the role of local monopsony, and allows competition and complementarity among workers with different skills to affect their aggregate productivity and wages. Immigrants, considered as a differentiated skill group and characterized by a different distribution across education-experience cells relative to natives, have nuanced and differentiated effects on native workers of different skill groups. Using a simple but flexible nested CES production function of different skill groups and equalizing workers' marginal product to wages, this approach derives exact log-linear wage equations. These equations allow estimation of key elasticity parameters regulating complementarity between worker types, particularly the immigrant-native elasticity of complementarity within each education-experience cell. This parameter is distinct from, but as important as, foundational elasticity parameters used by labor economists to estimate the education premium (e.g., Autor, Goldin, and Katz (2020)) or experience premium (Card and Lemieux (2001)), which are crucial in the literature. Finally, this approach enables us to calculate immigration's long-run wage effects on each native worker group by combining the immigrant-native elasticity with the education and experience elasticities in CES-derived formulas and the exogenous changes in the supply of labor driven by immigration.

Due to its versatility and insight, several policy papers have adopted this approach to evaluate the effects of new immigrants or removing undocumented immigrants on the wages of US natives (e.g., Greenstone and Looney (2010, 2014); Edwards and Ortega (2017)). Additionally, the finding of immigrant-native complementarity has spurred a subsequent literature examining whether task specialization and upgrading by natives in response to immigration accounts for such complementarity (Peri and Sparber (2009); Llull (2018b); Hunt (2017)).

Notice that the "factor-supply" conceptual approach has also been crucial in analyzing the labor market effects of education and technology using CES production functions (e.g., Goldin and Katz (2009)). This framework has been updated with recent data and extended to include additional skill groups (in Autor et al. (2020)) to better understand the evolution of the education premium after 2010. In this contribution, we do the same in the analysis of the effects of immigration on native wages and employment.

The original studies employing the national "factor-supply" approach (Borjas (2003), Ottaviano and Peri (2012) and Manacorda et al. (2012)) have not been updated, modernized or extended over time. This paper substantially advances this approach in four ways. First, we modernize the econometric methodology for estimating the immigrant-native elasticity of complementarity by using a novel Instrumental Variable (IV) approach (instead of the least squares estimation employed by the original papers). Our approach utilizes a skill-cell-based, rather than location-based, shift-share instrument that generates variation in immigrant labor supply across skills, which we combine with demographic-driven changes of native labor supply across skills. We demonstrate that our instrument satisfies power and validity requirements. Specifically, it strongly predicts post-2000 inflows and is uncorrelated with pre-2000 wage and employment dynamics, a key condition for identifying current immigration's effects on wages (Jaeger, Ruist, and Stuhler (2018)).

Second, by modeling labor supply we add new estimates of the impact of immigrants on native employment-population ratios, a margin not yet considered by the "factor-supply" approach, which assumed rigid native labor supply. By allowing native labor employment to respond to immigrant inflows, we can measure the "crowding out" or "crowding in" effects on natives in each skill group. Estimating both employment and wage effects provides a more comprehensive characterization of immigration's labor market effects and indicates positive complementarity as well as positive labor supply effects for native workers.

Third, we investigate the mechanisms underlying these effects by analyzing natives' occupational specialization and upgrading responses to immigrants in each skill cell. This analysis integrates insights from the occupational upgrading and task specialization literature (as in Peri and Sparber (2009)) into the national "factor-supply" framework.

Finally, we contribute to the literature by extending the analysis to more recent decades, focusing on the 2020-2023 period, characterized by immigration flows that differ in size and skill composition from those in previously studied decades.

Our four main findings are as follows. First, using our more credible IV approach, we estimate an average elasticity of substitution between immigrants and natives in the post-2000 period of around 16-20 in our preferred specifications. This implies a significant degree of immigrant-native complementarity, and our results consistently reject the hypothesis that natives and immigrants are perfect substitutes (i.e., inverse elasticity equal to 0). When we allow the immigrant-native elasticity to differ by education group, we find smaller values for college-educated workers (around 10). These estimates imply complementarity between immigrants and natives similar to what was estimated in Ottaviano and Peri (2012), which proves to be a remarkably robust result. Additionally, in recent decades, we find stronger complementarity between college-educated natives and immigrants.

Second, the 2SLS estimates of the effect of immigration on natives' employment-population ratio are statistically significant and between 0.04 and 0.065 percentage point in response to a 1% increase in immigrant employment. This positive native labor supply response to immigrant inflows is consistent with natives increasing their preferences for working, possibly as better and more desirable occupations become available to them.

Our third finding is that a 1% increase in immigrant labor supply led to a 0.12% to 0.21% increase in the relative communication/manual supply of tasks by natives and an implied occupational upgrading of natives towards occupations with higher pay. We estimate that an average 0.01% to 0.02% native wage growth for each 1% growth of immigrant supply can be attributed to natives shifting into better-paying types of occupations in response to immigration. Additionally, this occupational upgrading may explain the higher native labor supply if natives have preferences for communication tasks.

Finally, using these elasticity estimates, we calculate that the 2000-2023 inflow of immigrants increased the wages of less-educated natives (high school degree or less) by 2.6% to 3.4% and increased average wages for natives by 0.6 to 0.7%, depending on parameter specifications. This recent inflow had no significant wage effect on college-educated natives.

The rest of the paper proceeds as follows. Section 2 describes the data used and shows trends in recent immigrant inflows to the US by education group. Section 3 presents the framework for our estimation of the wage and employment equations and the key complementarity parameters between immigrants and natives. Section 4 shows our estimates updating Ottaviano and Peri (2012)'s results and includes preliminary estimates of the effect of immigration on the national employment-to-population ratio of natives using an elementary IV. Section 5 describes the new and improved IV strategy for identification of the key parameters, demonstrates the IV's robustness and validity, and presents the main 2SLS estimates. Section 6 presents estimates of occupational specialization and upgrading of natives in response to immigration. Section 7 calculates the effects of immigrant inflows during the 2000-2023 period on native wages and labor supply. Finally, Section 8 concludes the paper.

2 Data and recent trends in immigration

Before describing the model used to estimate the impact of immigration on US wages, we describe the data used and the evolution of immigration and US wages, by skill, over the period 1980-2023.

2.1 Data, variables and sample description

In defining and constructing our variables and sample, we follow Ottaviano and Peri (2012) and Borjas (2003). Employment and wage data are 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 from the 2005, 2010, 2015, 2019, and 2023 American Community Surveys (Ruggles, Flood, Sobek, Backman, Chen, Cooper, Richards, Rogers, and Schouweiler (2023)).

We construct two slightly different samples to build employment and wage measures. In both samples, we consider people aged 18 and older in the Census year of interest who are not living in group quarters and 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.

To build the 32 cells identified by different combinations of education and experience, as in Ottaviano and Peri (2012), we define four education groups using details on individuals' educational attainment: no high school degree, high school graduates, some college education, and Bachelor's degree or more. Relying on the assumption that people enter the labor force at the end of their education period, we define eight experience groups, from 0 to 40 years, grouping individuals into 5-year intervals of potential experience in the labor market.[5]

We consider two measures of labor supply. First, we build a measure of hours worked by calculating the hours of labor supplied by each individual working a positive number of weeks during the previous year, multiplied by the individual weight (PERWT), and aggregated within each education–experience cell. Alternatively, we compute the cell-specific employment level (i.e., count of employed people) by summing the person weights of all individuals in the cell who worked a positive number of weeks during the previous year. In each cell, we also compute the population by summing the person weights of all people belonging to each cell regardless of their working status. The population in the cell is a measure of maximum potential labor supply and is used to calculate employment-to-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, where weights are the hours worked by the individual times their person weight.[6] 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 foreign-born status is assigned to those individuals who are noncitizens or are naturalized citizens.

In the analysis of occupational specialization and upgrading in Section 6, we define measures of natives' task supply and occupational quality for each education-experience cell, which we now describe. For the former, we rely on data from the US Department of Labor O*NET database (`https://www.onetcenter.org/db_releases.html`), which measures the importance of various physical and language abilities for each occupation. In particular, since we measure the task content of each occupation in 2000, the first year in our sample

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

[6]Individuals' real weekly wages are 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.

period for which O*NET was available, we use O*NET release 7.0 from the database releases archive.[7] We aggregate task content measures of each occupation in 2000 into two broad task indices (manual and communication), which we then assign to each individual based on their occupation in each year, and finally aggregate to the skill-cell level in each year.

For this procedure, we begin by following Peri and Sparber (2009) in building and assigning task indices to each occupation. We focus on the *importance* (IM) values in the "Abilities" file available at the occupation level. Occupations in O*NET are classified using the O*NET-SOC taxonomy, so that, similarly to previous works, we merge these values to 2000 Census using the OCCSOC variable, relying on the linking procedure developed by Borjas and Cassidy (2019). Therefore, each individual in Census 2000 is assigned O*NET values based on their occupation. We then compute the percentile for each ability over the whole population in order to attach to a more meaningful interpretation to O*NET values (i.e., a given percentile p tells us that only p% of all workers in 2000 were supplying that ability less intensively, based on their occupation). We collapse these new percentile scores at the occupation level using a version of the 1990 Census Bureau occupational classification scheme that provides researchers with a consistent classification of occupations over time (OCC1990) so that we will be able to assign these scores to individuals in each year.[8]

Having assigned task scores to each occupation, we construct communication and manual task indices by aggregating different abilities as in Peri and Sparber (2009), and use these indices for each occupation across all years.[9,10] We then apply the same sample restrictions that we used to build the employment groups and compute the average of communication

[7] Version 7.0 (released in 2004) maximizes the number of matches between the O*NET occupation classification and the 2000 Census, while remaining sufficiently close in time to accurately capture the task content in place in 2000. Using O*NET 5.1 (the earliest version that O*NET advises researchers to use) or O*NET 11.0 (used by Peri and Sparber (2009)) changes our results minimally.

[8] Since occupations are merged or split over the decades, we choose the classification from 1990, the midpoint of our initial sample (from 1960 to 2019), limiting crosswalks and adjustments.

[9] We build the communication and manual skill indices according to the basic definition of Peri and Sparber (2009). The manual skill index is the average of the following O*NET variables: arm-hand steadiness; manual dexterity; finger dexterity; control precision; multi-limb coordination; response orientation; rate control; reaction time; wrist-finger speed; speed of limb movement; extent flexibility; dynamic flexibility; gross body coordination; gross body equilibrium; static strength; explosive strength; dynamic strength; trunk strength; stamina. The communication skill index is the average of the following O*NET variables: oral comprehension; oral expression; written comprehension; written expression.

[10] While there are no issues in the merge for post-2000 years, we rely on David Dorn's crosswalk based on a 1980-2005 balanced panel of occupations (using occ1990dd to classify occupations, see Autor and Dorn (2013)) to bring O*NET indices to earlier decades.

and manual task indices for native workers in each education-experience cell in each year, weighting by hours worked and person weights. We compute these indices separately for native men, women, and the pooled sample, as well as for their corresponding full-time worker subsets. We conclude by taking the ratio between the communication and manual task indices in each cell at each time t to capture the natives' relative task supply, which we use (in logs) as the outcome in the regressions of Section 6.

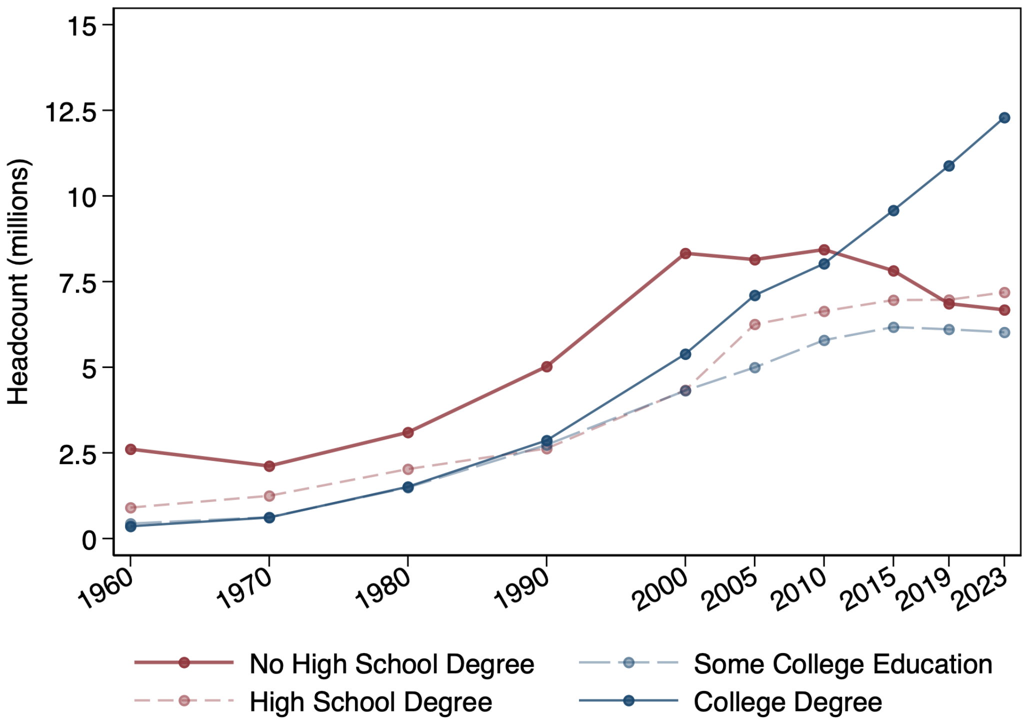
To construct our measure of natives' occupational quality, the other outcome used in these regressions, we apply our previously described sample restrictions to the 1980 US Decennial Census, the first period of our sample of analysis. We calculate the average wage by occupation in 1980 by averaging individual weekly wages (annual wage and salary income divided by weeks worked), and taking the weighted average using individual sample weights. Occupations are classified using the 1990 Census Bureau occupational classification scheme (OCC1990). We then use these 1980 occupation-specific average wages as a fixed measure of occupational quality, assigning to each individual in our full sample (both Decennial Census and ACS data) the average wage associated with their occupation in a given period. This approach treats occupational quality as time-invariant, reflecting the relative ranking of occupations established in 1980. Following our standard methodology for wage and employment measures, we aggregate this occupational quality variable within education-experience cells using individual worker weights. We compute this measure for natives only, with additional breakdowns by gender and full-time work status.

2.2 Immigration and wage trends

Figure 1 shows the evolution of the foreign-born adult population residing in the US between 1960 and 2023. The data are from the Decennial Censuses between 1960 and 2000 and then from the American Community Survey 2005, 2010, 2015, 2019 and 2023. 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 reveals significant differences in immigration patterns after 2000 compared to earlier decades. During the 1970-2000 period, immigrant populations across all education levels experienced consistent positive growth. Less-educated immigrants without high school degrees constituted the largest group and expanded at rates equal to or exceeding those of college graduates, while also outpacing the intermediate education categories. This pattern reversed dramatically after 2000. The population of immigrants without high school degrees not only stopped growing but actually contracted, implying negative net migration. Meanwhile, the population of immigrants with high school diplomas or some college education experienced slower growth rates and stabilized in size. In contrast, the number of college-educated immigrants continued to grow, even accelerating. By 2015, this highly educated group had become the largest group of foreign-born in the US adult population. The graph suggests that net immigration to the US shifted from large and relatively balanced across skills in the 1980-2000 period to smaller and more college-intensive in the 2000-2023 period.

Figure 1: Immigrant population by education group (1960-2023)



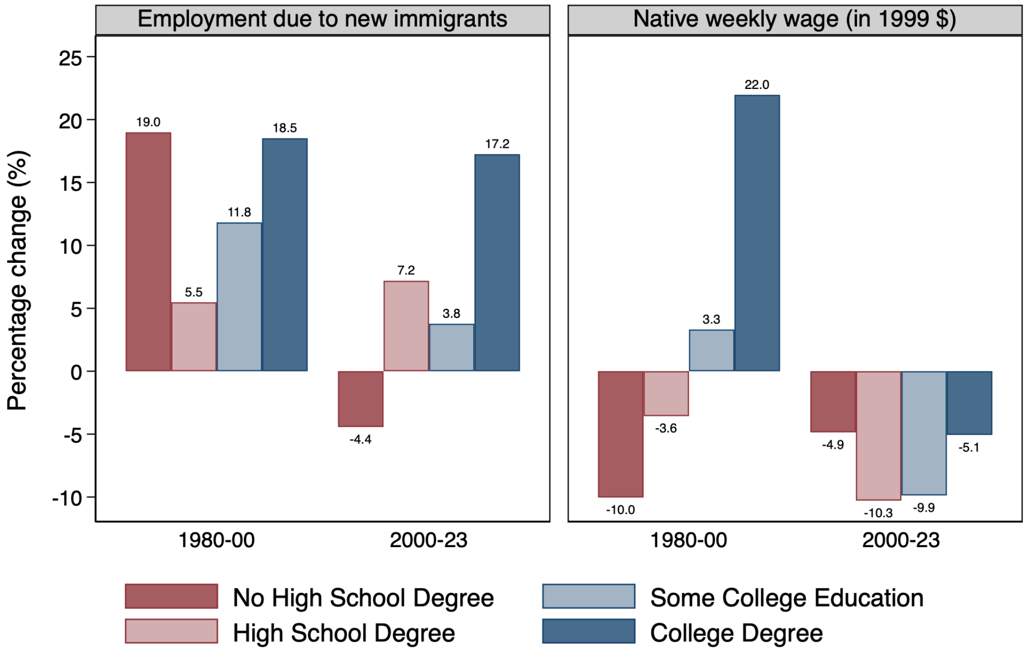
Notes: This figure depicts the evolution of the foreign-born population in the US by education group. The ten dates used for this figure correspond to those used throughout our analysis (1960, 1970, 1980, 1990, 2000, 2005, 2010, 2015, 2019, and 2023). We restrict the sample to foreign-born individuals aged 18 years and older.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

In Figure 2, we translate these population changes directly into percentage changes in labor supply for each education group, aggregating the periods 1980-2000 and 2000-2023. The left panel of the figure shows the percentage change in employment due to net immigration in each education group in each sub-period. The histogram shows a U-shaped pattern in the 1980-2000 period, with larger and comparable changes in immigrant supply for groups with college degree and no high school education, and smaller changes for intermediate groups. This pattern was noted earlier in Ottaviano and Peri (2012). During the 1980s and 1990s, the growth in labor supply due to immigrants was much larger (19% increase) for the least and most 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 2000-2023 period. First, the growth in each group's employment due to net immigration was much smaller. Second, the group of college graduates experienced the largest increase (+17% in 2000-2023) while the group with no high school degree experienced a *negative* change in employment due to immigrants (-4.4% in 2000-2023). Net immigration in the post-2000 years can be characterized as shrinking the supply of the least educated workers while significantly increasing the supply of college-educated ones.

For reference, the right panel of Figure 2 shows the percentage changes in native weekly wages for the same periods by education group. In the 1980-2000 period, percentage changes in native wages show a monotonic increase in dispersion, with wages for college-educated workers growing very fast and those for workers with no high school degree declining rapidly. The following two decades (2000 to 2023) exhibit less unequal growth across groups, with declining average wages and better wage performance for workers with no high school degree and those with a college degree compared to other groups. In neither period is there a negative association between immigrant-driven labor supply growth and changes in native wages, which a canonical model with four skill groups and perfect substitution of immigrants and natives would predict if immigration-driven supply of labor was an important factor in explaining wage dynamics.

Appendix Table 10 shows more detailed changes in the share of immigrants and in real wages across education-experience groups between 2000 and 2023. As was also the case in Ottaviano and Peri (2012) for the 1990-2006 period, there is no clear negative correlation between columns (3) and (4) of Table 10, revealing no prima facie evidence of pure wage-competition effects from increases in labor supply in each skill group due to immigration.

Figure 2: Changes in employment and native wages by education group



Notes: This figure presents percentage changes in employment due to net immigration (left panel) and percentage changes in real weekly wages of native workers (right panel), by education group. Changes over the 2000-2023 period, which are also reported in Appendix Table 10, are compared here to their corresponding values from the 1980-2000 period.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

3 Framework and estimating equations

3.1 Nested CES production function

The factor-supply framework we use follows the seminal papers by Borjas (2003) and Ottaviano and Peri (2012). We consider an aggregate national 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 can be 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 macro and growth models (such as in those presented in Chapters 1, 2 and 3 of Romer (2019)) to represent long-run production. The key modeling assumption to analyze the interplay between the 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.[11] Immigration changes the supply of different types of workers (skill cells) by changing the relative abundance of skills, and this affects skill-specific marginal productivity, which in the long run equals wages. The magnitude of these effects depends on the own and cross elasticities of substitution across skill groups and the relative change in the supply of each group. One important limitation of this approach is that we omit the potential effects of immigration on productivity in the analysis, which could be significant, especially in the presence of high-skilled immigration (see Peri et al. (2015) and Peri (2012)).[12]

Physical capital is complementary to aggregate labor, and in the long run, the capital-output ratio is constant (by equating the marginal productivity of capital to the long-run discount rate) and unaffected by immigration (consistent with Peri (2012), which estimates a negligible response of capital per worker to immigration inflows). Using this equilibrium condition for capital, one can simplify the production function so that total output is a linear function of the labor composite, multiplied by a modified TFP term. Hence, aggregate productivity growth is 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 can have an impact on the long-run wages of natives.

Following Goldin and Katz (2009) and Autor et al. (2020), we describe the labor aggregate L as 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, respec-

[11] This structure assumes that at the national labor market level firms are competitive in hiring and cannot be wage setters. While several studies have considered the monopsonistic power of firms in local labor markets (e.g. Manning (2021)), it makes sense to think that firms will operate competitively in a US-wide labor market.

[12] This approach also assumes symmetric "labor demand" effects of immigration through consumption, which, as shown in Galaasen, Kostøl, Monras, and Vogel (2025), are important. Specifically, in the regression analysis, we assume that the demand effects of immigrants are common within an education group and can be absorbed by education fixed effects. We do not develop an analysis that uses differences in demand effects across sectors.

tively, and σ_{HL} is their elasticity of substitution. We identify group H as workers with a college education or more, and group L as workers with a high school diploma or less. This is an important partition in this framework, as it reflects the very different labor markets faced by these two groups of workers. Over the last four decades, having a college education has been critical for accessing jobs and occupations with more intensive cognitive and analytical content, whose demand 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 a college education or more, we allow – as Ottaviano and Peri (2012) did – workers to be imperfect substitutes across narrow education groups, 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.[13]

Following Card and Lemieux (2001), Welch (1979), and several other papers that have analyzed the evolution of experience premium (age profile of wages) 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 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

[13] 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".

productivity equal to θ_{Dkj} and θ_{Fkj}, and elasticity of substitution equal to σ_N, as follows:

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

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 the experience premium (Card and Lemieux (2001)). Second, it is tractable and enables us to derive simple equations relating (log) wages to (log) employment for each skill group of workers to represent labor demand. These equations allow us to estimate the elasticity of complementarity between skill groups, provided we identify exogenous shifts of the supply of each skill group. Third, once we obtain, sequentially, the elasticity estimates across skills in the different nests of the CES, this model allows us to calculate the total impact of different historical immigration episodes on the long-run wages of native workers in each skill group. The calculated effects operate through changes in relative supply that affect the marginal productivity of different worker groups via complementarity and competition effects.

3.2 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 simple log-linear relationships 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:

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

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 for estimating σ_N – the crucial model parameter capturing the elasticity of substitution between immigrants and natives in the same education-experience labor market. The smaller this parameter is (i.e., the larger the complementarity), the more an inflow of immigrants will boost marginal productivity and demand for native workers. We can refer to $\frac{1}{\sigma_N}$ as the intensity of complementarity between immigrants and natives. If $\frac{1}{\sigma_N} > 0$, then native and immigrant workers are not purely competing (perfect substitutes) in the labor market, but have a degree of complementarity that increases as the estimate of this coefficient grows larger.

Assuming the 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 in $\left(\frac{L_{Fkt}}{L_{Dkt}}\right)$ is driven by changes in the relative population of those two groups, uncorrelated with cell-specific labor market conditions, then we can write equation (7) as follows:

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

Under these assumptions, a panel Least Squares estimation of equation (8) generates a consistent estimate of the "intensity of complementarity" $\frac{1}{\sigma_N}$. 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 analyses in terms of period, sample, and specifications to assess how robust those estimates were. We then advance this methodology by introducing a novel Instrumental Variable (IV) approach that captures cell-specific supply changes that are more likely to be uncorrelated with the relative productivity changes, $\frac{\theta_{Dkjt}}{\theta_{Fkj}}$, thereby reducing concerns about potential omitted variable bias. The parameter $\frac{1}{\sigma_N}$ is therefore more credibly estimated. Larger values of this parameter will produce larger positive wage impacts of immigration on natives.

Once $\frac{1}{\sigma_N}$ is estimated, one can construct the labor aggregate in equation (6), and use a similar log wage equation for each cell as a 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 elasticities of substitution σ_{HH},σ_{LL} and σ_{HL}. These 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 changes 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 premium, σ_{EXP}. Therefore, when calculating the total effects of immigration in Section 7, we will use a range of estimates for these parameters from the existing literature and will combine them with our newly estimated elasticity between immigrants and natives to obtain the total effects of immigration on the wages of each skill group of natives.

The model described above assumes competitive hiring in labor markets so that wages equate marginal productivity in the long run. While models with monopsony power and wage markdowns would lead to similar implications for the elasticity of substitution between natives and immigrants as long as native and immigrant markdowns are small, comparable across groups, or independent of immigrant labor supply, we maintain the competitive assumption for two main reasons. First, our analysis considers nationwide labor markets where the monopsony power of any individual firm is small. Second, the change in high-skilled immigration represents the main driver of supply variation in our estimates, and these workers exhibit high internal geographic mobility, making them less subject to strong employer bargaining power. Hence, the combination of national scope and worker mobility supports the assumption that competitive forces dominate wage determination in our context.[14]

3.3 Estimating the native labor-supply response

In the original factor-supply studies, the employment of US natives in each skill cell (k,j) was assumed to be constant, as if a fixed percentage of the working-age population in each skill group supplied work. Here, instead, we allow each US-born skill type to adjust

[14] Amior and Manning (2020) argue that immigration of less-skilled workers may affect wage markdowns. However, separately identifying the immigration's effects on both markdowns and immigrant-native elasticity of substitution requires strong functional form assumptions and proves highly sensitive to these modeling choices.

their labor supply, responding (positively) to wages paid to workers of their general skill level, W_k, and potentially to the presence of immigrants in their own labor market, L_{Fkjt}, according to the following labor supply curve:

$$Empl_{Dkjt} = Pop_{Dkjt} * \psi\left(L_{Fkjt}\right) * F(W_k) \tag{9}$$

In expression (9), Pop_{Dkjt} denotes the cell population, representing the maximum potential supply of labor, while the term $\psi\left(L_{Fkjt}\right) * F(W_k)$ captures the probability (fraction of full-time equivalent) that each individual in the cell supplies labor. The latter depends, through function $F(*)$, on wages paid to the broad skill group (education group) and, through function $\psi(*)$, on the presence of immigrants in the skill-specific cell. The perception that immigrants are crowding into the skill cell can induce US-born individuals to pursue more education (Hunt (2017)), or push people out of labor force (Borjas and Edo (2021)), reducing their labor supply; however, it can also steer US natives toward more desirable or preferred (cognitive-communication) tasks (Peri and Sparber (2011b)), or encourage them to enter the labor force (Cortés and Tessada (2011)), which would instead increase their labor supply.

We can use the simple expression (9) to derive an estimating equation for the long-run effects of immigrants on native labor supply. First, we can divide both sides of the expression by Pop_{Dkjt} and take a log linear approximation of the right hand side. Next, we can capture the dependence on skill-specific average wages, $F(W_k)$, with sets of education-experience and education-time specific fixed effects, $\phi_{kj} + \phi_{kt}$. They control for different education-specific wage change over time. Finally, we represent $\psi\left(L_{Fkjt}\right)$ with the log-linear expression $\beta_{emp} \ln\left(Empl_{Fkjt}\right)$. By so doing we obtain the following log-linear estimating equation:

$$\frac{Empl_{Dkjt}}{Pop_{Dkjt}} = \phi_{kj} + \phi_{kt} + \phi_{kj} + \beta_{emp} \ln\left(Empl_{Fkjt}\right) + e_{kjt} \tag{10}$$

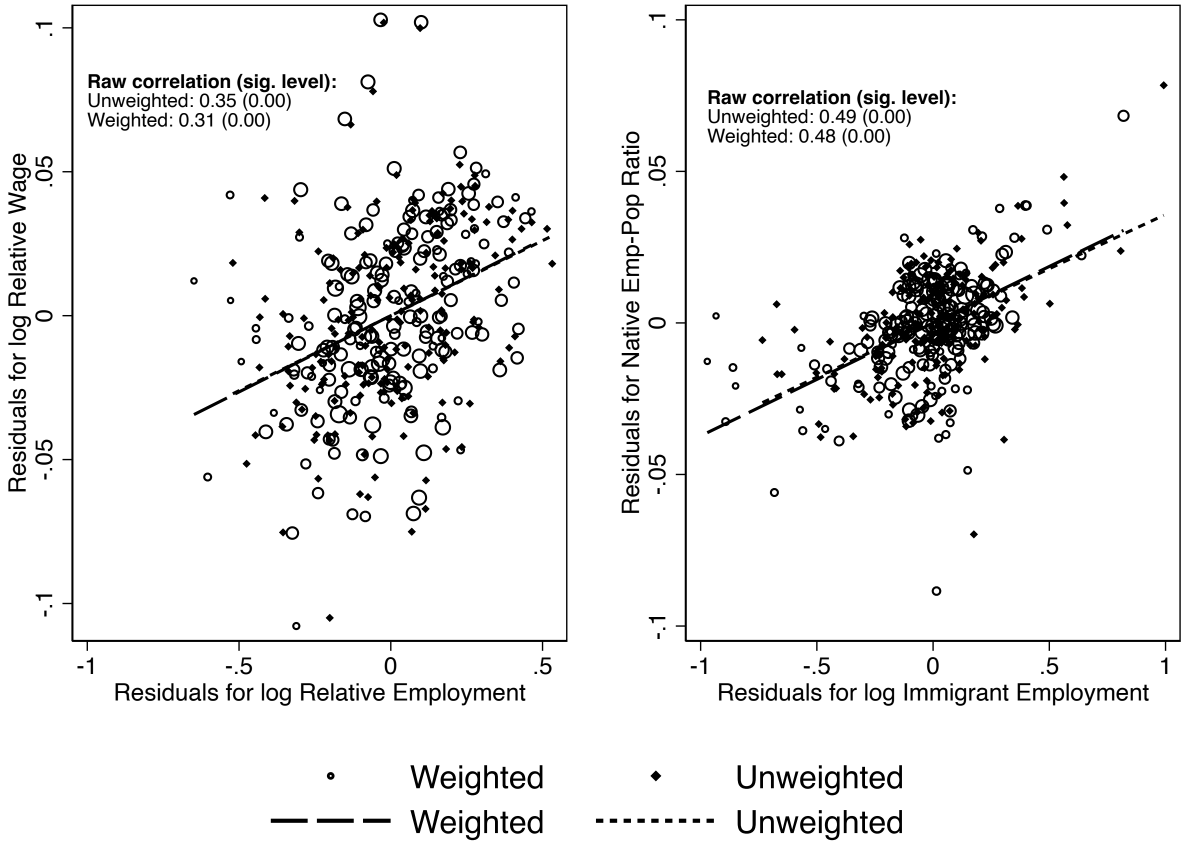
The coefficient β_{emp} measures whether immigrants generate additional crowding-in (if positive) or crowding-out (if negative) effects on similarly-skilled natives, beyond their potential wage effects at the skill-group level. By examining changes in natives' employment-population ratios, we can determine whether immigration serves as a catalyst for native labor market engagement or discourages participation. Our empirical strategy mirrors the approach used for wage effects in equations (8) and (10), employing comparable identification methods and instrumental variables to isolate exogenous variation in immigrant labor supply. The specification design creates a clean test: native employment rates serve as the dependent variable, while immigrant employment levels (in logs) constitute the key explanatory variable. This specification allows us to measure how immigrant "density" within specific skill cells influences native labor supply decisions at the same skill level. Hence, the framework captures an important mechanism through which immigration may affect native workers. This operates not merely through wage competition, but through broader labor market dynamics that either attract natives into employment or discourage their participation.[15]

4 Updated and Expanded Least Square Estimates

Before turning to formal regression analysis and addressing identification concerns, we examine the key correlations we are investigating by plotting skill-cell-level immigrant supply against native wages and employment outcomes. Figure 3 shows the relationship in the 2000-2023 period between changes in the (log of) relative native-immigrant wage and the (log of) relative immigrant-native employment in the left panel, and between changes in the native employment-population ratio and the (log of) immigrant employment in the right panel. Both panels include fitted regression lines and correlation statistics. To isolate the variation of interest, we plot the residuals obtained by regressing these variables on the main set of fixed effects we will use in our empirical exercise (education-by-experience FE and year FE) using the pooled men and women sample. The resulting values, therefore, represent deviations from period-means across cells. The positive and significant correlations between log relative immigrant-native employment and log relative native-immigrant wages, and between log immigrant employment and the native employment-to-population ratio, provide prima facie evidence consistent with both complementarity (i.e., imperfect substitution) between natives and immigrants and crowding-in effects of immigrants on native employment. In other words, in cells that are more "crowded" with immigrants, the relative wage of natives is higher, and so is their employment-population ratio.

[15] Appendix C presents robustness checks using alternative measures of immigrant supply, including foreign-born population shares rather than employment levels, to ensure our findings are not sensitive to specific variable constructions.

Figure 3: Correlation between main variables at the skill-cell level (2000-2023)



Notes: This figure plots the correlation between the residuals of the main variables of interest at the skill-cell level for the 2000-2023 period, using the pooled sample of men and women. The left (right) panel shows the relationship between relative wages (native employment-population ratio) and relative employment (immigrant employment), along with corresponding regression lines and correlation coefficients. The short-dashed (long-dashed) line represents the unweighted (weighted) regression line. Circle sizes are proportional to cell employment. The dates used for this figure correspond to those used throughout our analysis for the recent period (2000, 2005, 2010, 2015, 2019, and 2023). *Source:* ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

4.1 The native-immigrant elasticity of substitution

Table 1 shows estimates of the parameter $\frac{1}{\sigma_N}$ from equation (8) for different samples and specifications. Panel A uses decennial census data over the longer period 1960-2019, whereas Panel B uses quinquennial data for the more recent period 2000-2023 (5-year intervals, except for the last two periods of 4 years each). 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 either a longer period (Panel A) or focusing on the more recent period only (Panel B). In either case, the coefficient captures the intensity of complementarity between natives and immigrants, estimated including (or exclusively using) the more recent immigration period.

Notice that, as the dependent variable in equation (8) is $\ln\left(\frac{w_{Dkjt}}{w_{Fkjt}}\right)$, our estimates show the positive value of $\frac{1}{\sigma_N}$, while in Ottaviano and Peri (2012) the estimates reported were for the same coefficient but with a negative sign, $-\frac{1}{\sigma_N}$, since their dependent variable was $\ln\left(\frac{w_{Fkjt}}{w_{Dkjt}}\right)$.

Rows (1)-(4) in Panel A and Panel B follow exactly the same specifications, variable definitions, and estimation methods as the first four rows of Table 2, Panel A in 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 worked in a cell as the 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, while 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. Hence, by using population rather than employment as the explanatory variable (or IV), estimates in rows (5) and (6) should be less affected by unobservable cell-specific productivity shocks.

As for the column specifications, they differ in terms of worker samples and estimation methods. Specifications (1) to (4) include all workers with a positive number 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 workweek. Individual columns then differ in the set of fixed effects included and the weighting scheme used. Specifications (1) and (5) weight each cell by its employment and include no fixed effects; columns (2) and (6) include 32 cell fixed effects (education by experience) and year fixed effects; columns (3) and (7) use no weights; columns (4) and (8) include the most extensive set of fixed effects possible by including all two-way fixed effects (year-education, year-experience, and experience-year) in a “fully saturated” regression. This represents a more demanding specification than any used in the original analysis by Ottaviano and Peri (2012).

Several results emerge clearly from Table 1. First, focusing on the top four rows of

Table 1: New estimates of $(1/\sigma_N)$ 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: 2000-2023				
Men, Hours	0.026*	0.057***	0.053***	0.040	0.032*	0.064***	0.055***	0.045
	(0.016)	(0.015)	(0.012)	(0.037)	(0.017)	(0.016)	(0.013)	(0.037)
Women, Hours	0.043***	0.055**	0.044**	0.050	0.051***	0.063***	0.045*	0.056
	(0.012)	(0.022)	(0.022)	(0.036)	(0.012)	(0.022)	(0.024)	(0.037)
Pooled, Hours	0.033**	0.054***	0.051***	0.048	0.039**	0.060***	0.052***	0.052
	(0.015)	(0.017)	(0.012)	(0.033)	(0.016)	(0.018)	(0.013)	(0.033)
Men, Employment	0.027*	0.056***	0.055***	0.052	0.032*	0.064***	0.055***	0.048
	(0.015)	(0.016)	(0.012)	(0.040)	(0.017)	(0.016)	(0.013)	(0.037)
Men, Population	0.023	0.054***	0.055***	0.058	0.030*	0.057***	0.057***	0.058
	(0.018)	(0.015)	(0.013)	(0.040)	(0.018)	(0.015)	(0.014)	(0.042)
Men, Hours (IV)	0.021	0.055***	0.055***	0.055**	0.026*	0.058***	0.056***	0.053*
	(0.015)	(0.014)	(0.011)	(0.028)	(0.015)	(0.014)	(0.012)	(0.028)
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 seven data points (1960, 1970, 1980, 1990, 2000, 2010, 2019). Panel B considers the 2000-2023 period, using six data points (2000, 2005, 2010, 2015, 2019, 2023). Each coefficient of the table is estimated from a separate OLS regression, whose outcome is (log) relative weekly wage (for men, women or the pooled sample, depending on the row). In both panels, all specifications use (log) relative hours worked as the measure of labor supply (main regressor), except in rows (4) and (5), which instead employ (log) relative employment and (log) relative population, respectively. Row (6) instruments (log) relative hours worked with (log) relative population, and reports the resulting 2SLS estimate. Regressions in rows (1) through (4) are weighted by cell employment, while those in rows (5) and (6) use cell population as weights. 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). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

Panel A, which simply extend the estimates in Table 2 of Ottaviano and Peri (2012) to 2019, most of the coefficient estimates are significantly different from 0 and 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 those 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 coefficients values, close to 0.06. 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, highly significant and very precise. When capturing labor supply variation with changes in population only, the original results are fully confirmed and the precision of the estimates is still remarkable.

Panel B examines the same specifications using exclusively recent data from 2000-2023, a period that falls entirely outside the scope of the foundational studies (Borjas (2003), Ottaviano and Peri (2012), or Manacorda et al. (2012)). The results provide strong confirmation that native-immigrant complementarity persists in this contemporary period. Overall, the coefficients are very similar to those in Panel A, typically between 0.055 and 0.065, implying an elasticity of substitution between 16 and 20 in most cases. Similar to Panel A, even the most demanding specifications, including all two-way fixed effects and using population as an IV (final row, columns 4 and 8), yield statistically significant coefficients near 0.05. This contemporary evidence demonstrates that the complementarity relationship documented for earlier decades remains intact after 2000.

Finally, it is worth emphasizing that the estimated complementarity between natives and immigrants is robust. The estimated parameters remain stable across different samples, whether analyzing male workers, female workers, all full-time workers, or all workers. Furthermore, 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 7, the estimated value of this parameter implies substantial wage benefits for native workers from the increased inflow of college-educated immigrants, which particularly benefited non-college-educated natives. The current estimates suggest that this boost became stronger in the post-2000 period.

4.2 The native employment-population ratio response

The imperfect substitution between immigrants and natives within each skill group, demonstrated in the previous section, suggests that the marginal productivity of natives may increase, on average, in response to immigrant inflows. However, the wage effects represent only part of immigration's potential labor market effects. Some recent studies focusing on the impact of immigration on local employment (Dustmann et al. (2017); Amior (2020)) have emphasized possible displacement or crowding-out effects. These papers find that natives are less likely to migrate to local economies experiencing high immigrant inflows from other areas.

While such a mechanism could operate at the local level, our analysis of national effects internalizes mobility across locations for each skill group. Once local adjustments are accounted for, employment effects may differ substantially from those described in those studies. If the nature of available jobs becomes more desirable for natives due to specialization (e.g., Peri and Sparber (2011a)), native labor force participation for given wages may increase when more immigrants enter employment. This may imply native labor reallocation across occupations and areas, dynamics that would be missed in a local area analysis (as also pointed out in Foged and Peri (2016)). Additionally, our national analysis can capture employment effects that arise when there are complementarities between workers in different locations through trade relationships, effects that local area studies would miss entirely, as long as these complementarities operate only within skill cells

To test this, we analyze whether higher immigrant supply affects natives' employment-population ratio in the same skill group at the national level, as allowed in equation (10). Better jobs and a boost in expectations of labor market opportunities could draw more natives into the labor force and employment. Conversely, dislike of working with immigrants or fears of competition may decrease their participation. The analysis of this channel, operating through native labor supply, 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).

Therefore, we estimate the panel equation (10), where changes in native employment-population ratio depend on changes of immigrant employment in the skill-cell, after controlling for sets of fixed effects that capture average education-group and experience-group wages and their changes over time. Table 2 shows the effect of immigration on native employment rate, using specifications similar to columns (2), (3), (6) and (7) of Table 1 above. In addition to cell fixed effects, the more saturated specifications in columns (3) and (7) include education-by-year fixed effects to account for average wage changes across broad skill groups, which may be an important driver of labor supply observable by workers. Columns (4) and (8) take a similar approach, including education-experience and experience-by-year fixed effects instead. The explanatory variable in these regressions 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 main estimates for the 1960-2019 period, reported in Panel A, are highly statistically significant and range between 0.03 and 0.075 in the pooled (men and women) specification. This implies that a 10 log point increase in immigrants (about 10%) in a cell increased the employment-population ratio of natives by 0.3 to 0.75 percentage points. The effect is estimated to be similar, possibly marginally smaller, for the period 2000-2023 in Panel B, which shows highly significant estimates, between 0.025 and 0.056 for the pooled sample. The estimates remain positive and statistically significant even in the more saturated specifications shown in columns (3), (4), (7), and (8). Importantly, for the more recent period (2000–2023), the magnitudes are not substantially different, suggesting that our main specification that includes education-by-experience and year fixed effects provides a reliable estimate of the labor supply effect of interest. We will use similar specifications when implementing IV estimation in Section 5.

These estimates highlight two very important points. First, they reinforce the native-immigrant complementarity shown by the estimates in the wage regressions. As immigrant labor increases the value of native labor due to complementarity, and immigrants provide different tasks, natives become more willing to supply labor in the long run. Consequently, their employment-to-population ratio increases while the share of non-employed natives decreases. One important reason for this complementarity could be occupational specialization and upgrading by natives in response to immigration. We will investigate this mechanism in Section 6. Second, these results provide no evidence that immigration causes employment displacement or crowding out of natives at the national level. While local adjustments of native employment may still occur, these findings suggest that over a five-year horizon (estimates in Panel B) these adjustments ultimately result in higher national employment among natives with similar skills to immigrants. We show in Section 6 that immigration causes occupational reallocation among natives, which may entail geographic mobility or changes in natives' geographic employment patterns. Internalizing these transitions, our estimates indicate that immigration increases both employment and wages for native workers at the national level.

The existing studies examining employment effects of immigration in the US by skill group that are comparable to ours are Borjas (2003) and Monras (2020b). These papers use somewhat different specifications, with employment as the dependent variable rather than the employment/population ratio, and they focus only on the 1980s and 1990s, mainly analyzing responses to immigration from Mexico. The negative effects that they find for less educated US workers may therefore be driven by the specific time period and immigration shocks analyzed. As we do, Monras (2020b) finds positive effects of immigration on the employment of high-skilled US workers in the 1990s.

One important caveat is that we analyze aggregate labor markets rather than individual worker outcomes, which are not observable in our data. Some individuals may be displaced from work or experience reduced wages due to competition from immigrants. The differences in individual outcomes and aggregate labor market outcomes 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 with similar education and experience are attracted into employment or experiencing increased wages.

5 Reducing omitted variable bias: IV estimation

The estimates in Ottaviano and Peri (2012), as well as those in other studies using similar approaches (Manacorda et al. (2012); Borjas (2003); Borjas and Katz (2007a); Borjas, Grogger, and Hanson (2012)), limited themselves to least squares panel estimation of equation (8). They relied on including large sets of fixed effects to control for the correlation of the error term (productivity changes) with the explanatory variable (labor employment).

However, skill-cell-specific productivity shocks that may attract immigrants to the country are beneficial to native and immigrant wages. These unobserved shocks may induce

Table 2: Effect on native employment-to-population ratio

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	All workers				Full-time workers only			
	Panel A: 1960-2019							
Men, Imm. employment (IV)	0.070***	0.078***	0.022***	0.100***	0.071***	0.072***	0.016***	0.105***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)
Women, Imm. employment (IV)	0.078***	0.080***	0.045***	0.084***	0.112***	0.109***	0.044***	0.144***
	(0.010)	(0.012)	(0.008)	(0.010)	(0.012)	(0.012)	(0.014)	(0.013)
Pooled, Imm. employment (IV)	0.060***	0.060***	0.035***	0.065***	0.064***	0.062***	0.028***	0.075***
	(0.009)	(0.009)	(0.005)	(0.011)	(0.006)	(0.006)	(0.009)	(0.011)
F-stat (rows 1-3)	4280.41	3516.58	6748.62	2418.94	1779.85	1860.60	1699.66	1487.20
	Panel B: 2000-2023							
Men, Imm. employment (IV)	0.041***	0.041***	0.035***	0.046***	0.043***	0.036***	0.048***	0.030***
	(0.006)	(0.005)	(0.004)	(0.005)	(0.008)	(0.010)	(0.009)	(0.006)
Women, Imm. employment (IV)	0.037***	0.032***	0.013*	0.061***	0.058***	0.039***	0.016	0.100***
	(0.006)	(0.008)	(0.008)	(0.009)	(0.012)	(0.012)	(0.010)	(0.020)
Pooled, Imm. employment (IV)	0.037***	0.036***	0.025***	0.050***	0.044***	0.035***	0.030***	0.056***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.008)	(0.007)	(0.010)
F-stat (rows 4-6)	3452.79	2751.81	2274.47	1705.23	2851.77	1190.28	1284.39	1553.05
Weights	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Edu-Exp FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	-	-	Yes	Yes	-	-
Edu-Year FE	No	No	Yes	No	No	No	Yes	No
Exp-Year FE	No	No	No	Yes	No	No	No	Yes

Notes: Panel A considers the 1960-2019 period, using seven data points (1960, 1970, 1980, 1990, 2000, 2010, 2019). Panel B considers the 2000-2023 period, using six data points (2000, 2005, 2010, 2015, 2019, 2023). Each coefficient in the table is a 2SLS estimate from a separate regression. The outcome variable is the ratio between native employment and native population (for men, women, or the pooled sample, depending on the row), while the main regressor is (log) immigrant employment, instrumented with (log) immigrant population. First-stage F statistics are reported. Cell employment is used as weight. Robust standard errors are clustered at the cell level (education by experience). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

spurious correlations between relative wages and immigrant labor supply in a cell, generating a positive or negative bias depending on whether they affected immigrant productivity in the skill cell more or less than native productivity. Identifying variation in immigrant population that is less correlated with unobservable skill-specific productivity shocks can reduce such omitted variable bias.

Most of 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 historical settlement patterns of immigrants from different origin countries across US locations, combined with large changes in flows of immigrants from specific origins over time, to identify variation in location-specific immigration flows that is exogenous to local economic trends.

While we cannot apply the same location-based network approach in this context, we adapt this logic by using persistent characteristics of immigrants from each origin country, specifically their education and age profiles, interacted with the changing flows by origin over time, to construct a shift-share instrument that captures variation in immigrant labor supply across skill cells.

We are aware of only three papers that generate an instrument for national immigration by education-experience cells using variation in origin push-factors interacted with demographic groups. The first is Monras (2020a), which relies on the "Peso crisis" in the 1990s that affected the Mexican immigration to the US. This was a specific shock, mainly affecting less-educated, young immigrants, and cannot be used in a general approach extended to the post-2000 period. The second is Llull (2018a), which exploits origin country shocks such as wars, political regimes, natural disasters, and economic crises to generate push-driven variation in migration from those countries, which is then interacted with distance and skill-group dummies to obtain group-specific imputed immigrant populations. The instruments are used in that study to estimate the partial effect of immigration on native wages. While the asymptotic and econometric properties of the IV are carefully analyzed, Llull (2018a) does not consider imperfect immigrant-native substitution, the total wage effect (accounting for complementarities) of immigrants, or employment effects in his analysis. Finally, Amior and Manning (2020) use an instrument based on demographic changes of natives and push-factors from origin countries (similarly to Llull (2018a)) to re-estimate the elasticity of substitution between immigrants and natives separately from a possible wage markdown on wages. Our approach is closer to a more standard shift-share method, and we subject it to pre-trend tests to show that the changes in relative supply generated by our IV are not correlated with pre-1980 variation in relative supply and wages. We think our instrument represent a contribution relative to those previously used in this literature, especially in its simpler approach and for the validity tests we perform.

5.1 A shift-share IV for cell-specific immigrant labor supply

The characteristics of immigrants to the US vary significantly depending on their country of origin, particularly in terms of age and education level. For instance, while Mexican and Central American immigrants typically migrate to the US at a young age (mainly between 20 and 35 years old) and are selected among those with low levels of schooling (typically less than a high school diploma), immigrants from India tend to move when slightly older (between 30 and 40) and tend to be highly educated (college degree or more). Chinese immigrants, on the other hand, are distributed more uniformly across education groups. These differences in the skill composition of immigrants are partly driven by different selection mechanisms into migration due to varying gains across groups, depending on persistent differences in the earnings distribution between the origin and the US, as predicted, for instance, 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* in the pre-1980 period (or pre-1970 in a robustness check), and allocates more recent inflows from each origin across skill cells in the US labor market proportionally to that pre-determined distribution. Variation in labor supply across skills is generated by the changing pattern of origin countries over time. For instance, as Mexican immigration declined in the post-2000 period while immigration from India increased, our instrument would predict a decline in labor supply for young, 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, and aggregate all other countries by continent.[16] This leaves us with 12 selected origins: the 5 top countries - i.e., Mexico, Cuba, China, Philippines and Korea - and 7 continents (or broad geographic regions) - i.e. the remainder of North America, Central America and Caribbean,

[16]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 the Online Appendix.

South America, Europe, Africa, Asia and Oceania.[17] We then use these 12 groups (henceforth referred to 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:

$$sh_{kj}^{c} = \frac{\Delta^{80,60} pop_{kj}^{c}}{\Delta^{80,60} pop^{c}} \tag{11}$$

where $\Delta^{80,60} pop$ represents 1960-1980 net immigration for the group from origin country c residing in the US. In the numerator, the net change is computed for each individual skill cell, while the change in the denominator aggregates total net immigration from country c. With 32 cells for each origin country (4 education cells by 8 experience cells), we encounter a few cases with a negative cell-specific net flow (i.e., a negative numerator in expression (11)). This occurs when inflows of individuals from country c in a given cell did not compensate for 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 used to generate the denominator of (11). This correction allows us to obtain:

$$sh_{kj}^{c} \geq 0 \ \forall \{c,k,j\} \text{ and } \sum_{\{k,j\}} sh_{kj}^{c} = 1 \ \forall c \tag{12}$$

Next, for each country, we compute 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 changes for each cell as follows:

$$\Delta^{\widehat{t,t-10} pop}{}_{kj}^{c} = sh_{kj}^{c} * \Delta^{t,t-10} pop^{c} \qquad \forall t \in \{1990, 2000, 2010, 2019\} \tag{13}$$

The imputed changes from (13), 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 origin countries to obtain the imputed foreign-born (F) supply change in each education-by-experience cell:

$$\Delta^{\widehat{t,t-10} pop}{}_{kj}^{F} = \sum_{c} \Delta^{\widehat{t,t-10} pop}{}_{kj}^{c} \tag{14}$$

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

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

supply measures (in this case, foreign-born employment), by summing the initial immigrant population of each cell in 1980 and the cumulative imputed supply change of the cell for all decades up to τ as follows:

$$\widehat{(pop^F_{kj})}_\tau = (pop^F_{kj})_{1980} + \sum_{t=1990}^{\tau} \Delta^{t,t-10}\widehat{pop}^F_{kj} \quad \text{with } t \in \{1990, 2000, 2010, 2019\} \tag{15}$$

In $\tau = 1980$ we simply have $\widehat{(pop^F_{kj})}_{1980} = (pop^F_{kj})_{1980}$. We use the measure constructed as in equation (15) to instrument for foreign-born employment.

When we consider the period 2000-2023, we repeat the same procedure, obtaining country-specific imputed changes for 2005, 2015 and 2023. We drop observations before 2000, obtaining six imputed 5-year changes (i.e., for 2000, 2005, 2010, 2015, 2019 and 2023).

5.2 Demographic change as predictor of native cell supply

Since the explanatory variable in equation (8) is the (log of the) ratio of immigrant to native employment, we also instrument the variation in native population across cells. We proxy for native population change by predicting the demographic 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 the previous decade's native population in the group with the same education level k and with experience $j-10$ years. For instance, the native population of the group of individuals with a 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 a high school degree and 25 years of experience in 2000, and so on. Hence, we follow age cohorts within each education level to construct this variable.

In so doing, we project the size of each cell forward to the following decade (or 5-year period when considering the 2000-2023 interval), adding 10 (or 5) years to their experience group, while leaving the education structure unchanged. Since we cannot impute exact population size from the past for the two youngest groups (between 0 and 5, and between 5 and 10 years of potential experience), as 5 to 10 years earlier that cohort had not completed education, we rely instead on the education structure of the youngest cohort in the previous period. Specifically, we take the total population of natives with 0 to 5 and 5 to 10 years of potential experience 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.[18] We refer to this approach as the *one decade-ahead prediction* for each cell.

5.3 Power and validity of the instruments

Once we have constructed the predicted immigrant (foreign-born F) population, $\widehat{(pop_{kj}^{F})}_t$, with the shift-share method described in Section 5.1, and the predicted native (domestic D) population, $\widehat{(pop_{kj}^{D})}_t$, with the demographic projections described in Section 5.2, we are ready to build two instruments.

The first, $\ln \frac{\widehat{(pop_{kj}^{F})}_t}{\widehat{(pop_{kj}^{D})}_t}$, will be used in equation (8) as an instrument for $\ln\left(\frac{Empl_{Fkjt}}{Empl_{Dkjt}}\right)$ to estimate the parameter $\frac{1}{\sigma_N}$; the second, $\ln\widehat{(pop_{kj}^{F})}_t$ will be used in equation (10) as an IV for $\ln(Empl_{Fkjt})$ to estimate the parameter β_{emp}.

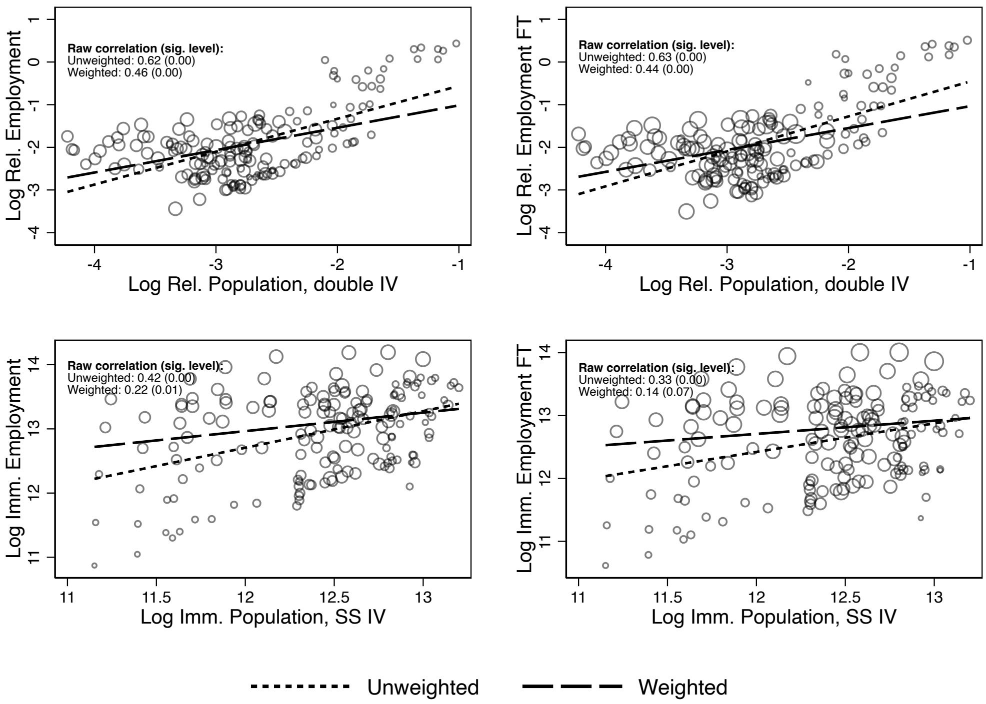
5.3.a Power

The panels of Figure 4 show the first-stage correlations of the two instruments with changes in labor supply for the 1980-2019 period. The top left panel shows the 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. Both panels report regression lines (short-dashed line for the unweighted case and long-dashed for the weighted case). A strong positive correlation is visible in both cases. This strong correlation translates into the high first-stage F statistics reported in columns (1) and (3) in Panel A of Table 4, equal to 71.6 and 92.1 for the specifications using weights. These statistics capture the partial correlation of the IV after controlling for the set fixed effects we use in the analysis.

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) and full-time workers only (right panel). A positive correlation is visible here as well, albeit weaker than in the top panels. The F statistics for these first-stage partial correlations from Panel B of Table 4 are 16.2 and 15.9 when observations are weighted. Overall, the first-stage F statistics for both panels are above the standard threshold of 10, below which concerns about weak instruments emerge.

[18] Since for the 2000-2023 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. We do so by using the education shares of the youngest cohort observed 5 years earlier.

Figure 4: First-stage relationships for Table 4

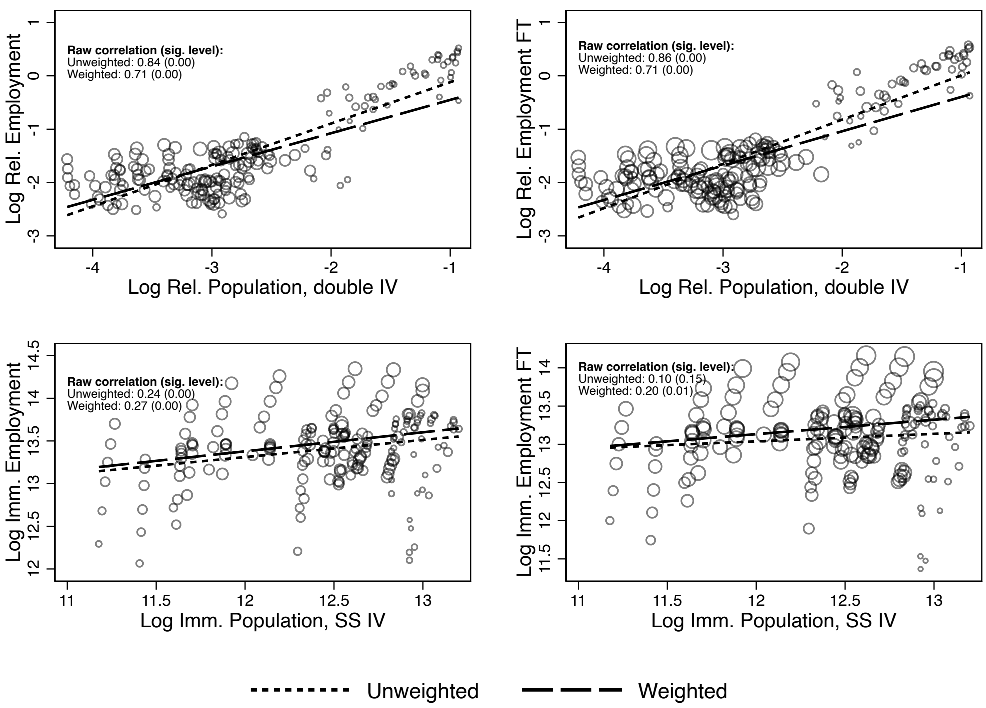


Notes: The upper-left figure refers to the first-stage relationship for the 2SLS coefficients reported in columns (1) and (2) of Panel A in Table 4. The upper-right figure refers to those in columns (3) and (4) of Panel A. The bottom-left figure to those in columns (1) and (2) of Panel B. The bottom-right figure to those in columns (3) and (4) of Panel B. Raw correlation coefficients are reported along with their significance levels. The short-dashed (long-dashed) line represents the unweighted (weighted) regression line. Circle sizes are proportional to cell employment.

The panels of Figure 5 show the same first-stage correlations as in Figure 4, but are constructed for the more recent period 2000-2023. The top panels show the correlation between the (log of) imputed population ratio and the (log of) employment ratio, including all workers in the left panel and full-time workers only in the right panel. 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 panel. Visual inspection of the raw correlations in Figure 5 reveals a positive but slightly weaker correlation of the IV with (log of) immigrant employment compared to the earlier period, and a positive strong correlation of the IV with (log of) relative employment. Table 5 shows that the power to predict relative employment is, in fact, somewhat weaker once we control for the fixed effects (F statistics equal to 24.9 and 35.4 when using weights), while the IVs predicting foreign-born employment are somewhat stronger (F statistics equal to 53.4 and 47.9 when using weights). For the 2000-2023 period as well, the first-stage F statistics of both panels exceed the conventional threshold, reassuring us against concerns about weak instruments bias.

Since our regressions feature a single endogenous regressor, we can apply the relative asymptotic bias test for weak instruments by Olea and Pflueger (2013), which is more appropriate in the 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 in Tables 4 and 5, except for those in Panel B of Table 4, which should therefore be interpreted with some caution.

Figure 5: First-stage relationships for Table 5



Notes: The upper-left figure refers to the first-stage relationship for the 2SLS coefficients reported in columns (1) and (2) of Panel A in Table 5. The upper-right figure refers to those in columns (3) and (4) of Panel A. The bottom-left figure to those in columns (1) and (2) of Panel B. Th bottom-right figure to those in columns (3) and (4) of Panel B. Raw correlation coefficients are reported along with their significance levels. The short-dashed (long-dashed) line represents the unweighted (weighted) regression line. Circle sizes are proportional to cell employment.

5.3.b Validity

In adopting a shift-share type of IV as we do, 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, persistent cell-specific labor market trends that may continue to influence wages and employment in the post-2000 period.[19] Previously, we noted that aggregate immigrant inflows changed significantly after 2000, characterized by large declines in Mexican immigration alongside increases in Asian immigrant inflows. This changing origin-country composition generates the post-2000 variation for our IV. Given that we newly estimate the post-2000 native-immigrant complementarity and the related effects of immigration using this variation, establishing the validity of our approach requires testing that these new flows are uncorrelated with pre-existing, skill cell-specific labor market trends.

First, we examine this correlation visually in the two panels of Figure 6. The left panel displays the relationship between the 2000-2019 changes in our (logged) relative-population instrument (horizontal axis) and the stacked 1980-1990 and 1990-2000 changes in log relative wages (vertical axis). The right panel shows the scatterplot of the 2000-2019 changes in our (logged) immigrant-population instrument (horizontal axis) against the stacked 1980-1990 and 1990-2000 changes in native employment-population ratio (vertical axis). In both panels, the units of observation are education-experience cells, and the correlations are shown after controlling for education and decade fixed effects. 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 the corresponding least squares regression lines (dotted for the unweighted regression, dashed for the weighted regression) and the least squares coefficients (captured by the slope) along with their p-values.

The visual evidence in Figure 6 demonstrates the absence of meaningful correlations between our instruments and pre-existing labor market dynamics, with both panels revealing statistically insignificant relationships. This evidence is shown more systematically in

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

Table 3, where we report the least squares estimates of regressions of changes in labor market outcomes (1980-1990 and 1990-2000, stacked) on the IV-imputed population changes (2000-2019). The outcome for columns (1) to (4) is the (log of) relative wage of natives, while the outcome for columns (5) to (8) is the native employment-population ratio. Columns (1), (2), (5), and (6) do not include fixed effects, while column (3), (4), (7), and (8) control for education and decade fixed effects (4 education groups and 2 decades). The results support the validity of the instrument. 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.[20] After showing that the constructed IVs exhibit reasonable power, these results provide strong evidence for the validity of our instruments by demonstrating that they are uncorrelated with pre-2000 labor market trends.

Additionally, we perform two robustness checks to address concerns that the variation captured by our IV may be driven by specific skill-cell demand shifts, such as technological changes associated with immigrant inflows from specific countries for specific jobs (e.g., Indian immigrants in tech jobs), resulting in positively biased estimates. The first robustness check involves constructing a leave-one-out shift share IV, systematically excluding each major country of origin from the instrument construction process. This approach ensures that our findings are not driven by a large demand-driven exodus from one specific country. The second validation exercise is obtained by constructing the initial skill-share across countries by using only the 1960-1970 decade, further removed from the post-1980 period of analysis and less likely to be correlated with post-1980 and post-2000 demand shocks. We show in Section 5.4 that both of these robustness checks yield estimates very similar to our baseline results, providing strong evidence that our identification strategy successfully isolates supply-driven immigration variation rather than demand-side technological factors.

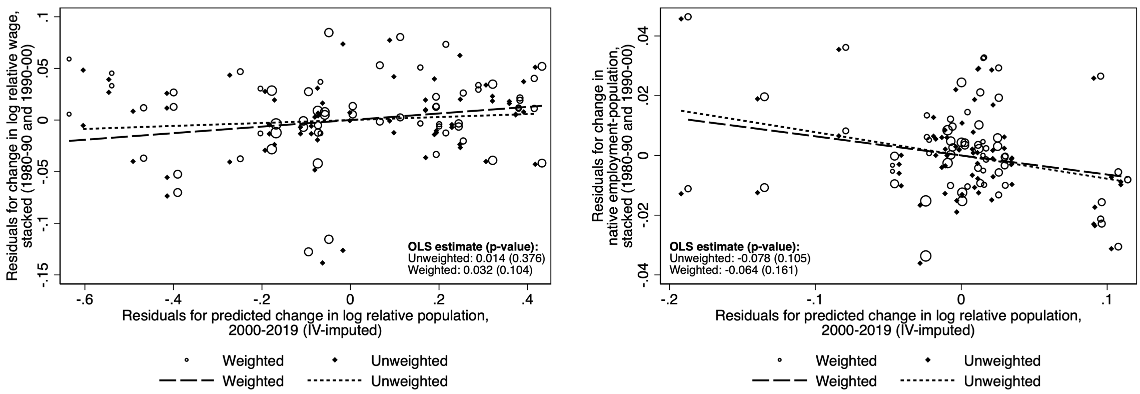
5.4 2SLS estimates

Tables 4 and 5 present our main IV results. Panel A reports estimates of $\frac{1}{\sigma_N}$, which captures the degree of productive complementarity between native and immigrant workers within skill cells. Panel B shows the estimates for the labor supply response coefficient β_{emp}, which

[20]Including fixed effects as we do in all our specifications seems to help absorb the small correlation between the instruments and pre-2000 relative wages, as also shown in Figure OA1 in the Online Appendix.

Figure 6: Pre-trends in outcomes

(a) Relative wage (b) Native emp-pop ratio



Notes: This figure plots the correlation between residual changes in outcomes of interest before 2000 and residual changes in the corresponding IV measures after 2000, by skill cell, after controlling for education and decade dummies. The left (right) panel displays residuals for 1980-1990 and 1990-2000 stacked changes in log relative wages (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, along with corresponding p-values, are reported. Unweighted regressions are represented by dotted lines (associated with black diamond markers), while weighted regressions are shown by long-dashed lines (circles). Circle sizes are proportional to 1980 cell employment (used as weight).

Table 3: Instrument validity - OLS estimates of the effect of IV on pre-trends in outcomes

	(1) Δ Wage	(2) Δ Wage	(3) Δ Wage	(4) Δ Wage	(5) $\Delta\frac{Emp}{Pop}$	(6) $\Delta\frac{Emp}{Pop}$	(7) $\Delta\frac{Emp}{Pop}$	(8) $\Delta\frac{Emp}{Pop}$
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 from regressions of stacked changes for 1980-1990 and 1990-2000 in the outcomes of interest (log relative wage in the first four columns, and native employment-population ratio in the last four columns) on 2000-2019 changes in the corresponding IV-imputed population measures (log relative population and log immigrant population, respectively). Observations are education-experience cells. Cells are weighted by 1980 cell employment. Robust standard errors are reported in parentheses.

captures whether immigration generates crowding-out effects that discourage native labor force participation or crowding-in effects that encourage it, as reflected in changes to native employment-population ratios. All specifications are estimated with two-stage least squares with controls for skill-cell and year fixed effects. The sample used in rows (1), (2), and (3) of each panel includes men, women, and the pooled sample, respectively, for constructing the outcome variable. Table 4 is estimated over the extended period from 1980-2019, while Table 5 only includes data for the more recent period from 2000-2023. The column estimates differ due to weighting (columns (1) and (3)) or not weighting (columns (2) and (4)) by cell employment, and by worker sample (including all workers in columns (1) and (2), or full-time workers only in columns (3) and (4)).

Overall, the key results from the least squares estimations are confirmed in these specifications, albeit 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 5 show that the same coefficient estimated for the two most recent decades is larger and always statistically significant. Its values range between 0.058 and 0.065 when estimated on the pooled sample. While the 2SLS estimates have somewhat larger standard errors (around 0.025) relative to OLS (around 0.01), most estimates in Table 5 reveal a significant degree of imperfect substitutability and an elasticity between natives and immigrants around $16-20$ for the period 2000-2023, consistent with the original estimates 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 Panel B of both Tables 4 and 5 reveals a significant positive response of natives' employment-population ratio 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, with particularly large values for full-time workers (especially women) in the 1980-2019 period. The effects are always statistically significant at the 5% level (and in most cases at the 1% level). The estimates for the more recent period (2000-2023) for the pooled sample are between 0.036 and 0.065, which is also consistent with the least squares estimates. We will use these as our reference values.[21]

The estimated positive effects on the employment-population ratio contradict some existing local estimates that suggest crowding out of natives in response to immigration at the local level (Dustmann et al. (2017); Amior (2020)).[22] However, there are several reasons why the complementarity effects of immigrants could 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 imply reallocation of workers across commuting zones. The national approach, as explained by its early advocates such as Borjas (2003), therefore may be a better approach to internalize those effects and produce more useful estimates for evaluating the national impact of immigrants on employment and wages. As also shown in Foged and Peri (2016) for Denmark, natives likely adjust to immigration through changes in firm and location to better take advantage of the complementarity and aggregate demand effects generated by immigrant inflows. This response pushes some of the beneficial employment effects outside the initial location of those inflows. Second, our framework is more careful in differentiating among workers' skills and substitutability-complementarity patterns, rather than treating all workers as one type of undifferentiated labor in a local labor market (as in Amior and Manning (2020)). Third, our effects are identified by the variation of immigrant supply across skills, not across regions, making them less subject to the confounding effect of local unobserved economic trends. Finally, the composition of immigrant inflows in the post-2000 period may contribute to differences in our findings. A large portion of immigrant inflows after 2000 were highly skilled, while most of the "monopsony literature" has focused on the impact of low-skilled or undocumented immigrants (see Borjas and Edo (2023) or Amior (2020)), whose numbers did not grow substantially between 2000 and 2023. Ultimately, while we believe local analyses shed light on important mechanisms, we also think that the present framework, focused on a national analysis across skill groups,

[21] In Appendix C, we also estimate specifications that are closer to those used in some earlier works, such as those in Borjas (2003) and in Monras (2020a), using the foreign-born population share in the cell as the explanatory variable. The estimates obtained using those specifications are fully consistent with our preferred specification.

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

is better suited for inferring national labor market effects of immigration.

One important consideration is that inference may not be reliable when instruments are weak. Hence, we might be concerned about some specifications where the instrument, although not weak, is not particularly strong. We consider two main alternatives, discussed in Davidson and MacKinnon (2010), to obtain more reliable inference. One approach is to employ the wild bootstrap method to calculate standard errors, which generally performs better than traditional bootstrap procedures (Cameron and Trivedi (2022)). Another approach is to use statistics with better properties, such as the well-behaved Anderson-Rubin (AR) test, which is the preferred method in a just-identified model like ours and, crucially, is designed to accommodate weak instruments.

We apply both approaches to test the robustness of each 2000-2023 estimate from Table 5. In Appendix Table 11, we report the p-values obtained by adopting three bootstrap methods. For wild bootstrap procedures, we explore two possibilities for choosing the weights on the residuals: the standard Rademacher weights and the common alternative of Webb weights. For the AR test, we provide a wild bootstrap version of the test.[23] Panel A of Appendix Table 11 shows that the coefficient for the elasticity of substitution estimated for the two most recent decades is statistically significant, as was the case in Table 5. Similarly, Panel B confirms the strong significance of our previous labor supply estimates, with very low p-values for all methodologies employed.

Furthermore, we test the sensitivity of our estimates to alternative constructions of the instrument to address concerns about confounding pull factors that both raise productivity for particular skills and attract immigrants from certain origins. First, we implement a leave-one-out version of the immigrants' shift-share instrument to make sure no single country (whose migrants may be motivated by specific jobs) drives the results. Appendix Table 12 replicates the main estimates for the 2000-2023 period (pooled sample only), excluding one of the five major sending countries (Mexico, Cuba, China, the Philippines, or Korea) in turn from the shift-share IV. A related concern is that post-1980 US pull shocks may be correlated with pre-1980 changes in education specialization by origin country. To address this, we per-

[23]Wild bootstrap methods perform well when used with other test statistics too, in particular with AR (Davidson and MacKinnon (2010)).

form a robustness check in which the shares of the shift-share IV are constructed using 1960-1970 changes in origin-specific skill composition of inflows, further lagging the reference period to help mitigate concerns about persistent omitted factors. Appendix Table 13 replicates the main estimates for the 2000-2023 period using these modified instruments. In both cases, our results remain remarkably stable. Finally, we perform a robustness check for the natives' demographic IV, which we leave for the Online Appendix. Since prior work has documented mortality differentials among natives with different skills (e.g., Buckles, Hagemann, Malamud, Morrill, and Wozniak (2016)), we construct mortality-adjusted cohorts for the demographic IV to avoid potential overestimation of natives in low-skill cells.[24] Repeating the analysis with this adjustment, we find that our estimates from Table 5 remain unchanged.

In Table 6 we extend our 2000-2023 estimates a step further, allowing for heterogeneity in the immigrant-native elasticity of complementarity across education groups. Specifically, we interact both the explanatory variable and the instrument with education-group dummies to estimate a different coefficient for each of the four education groups (no high school diploma, high school diploma, some college education, and college degree or more). Table 6 shows the results for the wage complementarity coefficients (Panel A) and for the employment-population ratio response coefficients (Panel B). Since these regressions feature multiple endogenous explanatory variables, caution is needed in interpreting the coefficients, even though inspection of the sizes of Shea's partial R^2, first-stage F statistics and the Sanderson–Windmeijer corrected conditional F statistics for first-stage regressions of each endogenous regressor does not indicate a weak-instrument problem.[25]

Panel A of Table 6 shows important patterns in complementarity coefficients across education groups. In most specifications, complementarity is stronger for individuals without a high school diploma, and even stronger (especially for full-time workers) for college graduates, the least and the most educated groups. The specifications estimated on the sample of all workers (columns (1) and (2)) show coefficients around 0.1 for the most and least

[24] To construct the mortality rate of each demographic group, we use estimates developed by the Wharton Budget Model initiative at the University of Pennsylvania, which combine CDC 1996-2017 death records with CPS population data (data are available at: https://budgetmodel.wharton.upenn.edu/issues/2020/7/6/mortality-gap-by-education).

[25] In the Online Appendix, we report several test statistics used to detail the nature of any weak-instrument concerns for Table 6 (Cameron and Trivedi (2022)).

Table 4: 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 the pooled sample) is regressed on (log) relative employment, instrumented with the imputed relative population, which is constructed as 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. First-stage F statistics are reported. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

educated groups, while they are 0.02-0.04 for the two intermediate groups. This pattern is strongly consistent with existing evidence on task specialization, which shows that immigrants differ most from natives at the two ends of the education spectrum. This distinction is pronounced in low-education job types, where immigrants are employed in occupations requiring manual- and physical-intensive tasks in personal, food, healthcare services (Peri and Sparber (2009)), and even more so among college-educated, where immigrants tend to take Science, Technology and Engineering jobs rather than in law, communication, sales and human resources (Peri and Sparber (2011b); Peri et al. (2015)). We will use these complementarity parameters differentiated by education group in our simulation in Section 7 to show their implications for native wages, particularly as immigration inflows have

Table 5: 2SLS estimates for elasticity of substitution and labor supply effect, 2000-2023

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Elasticity estimates (2000-2023)				
Men, Rel. employment (SS IV + demogr. IV)	0.047**	0.043*	0.051**	0.043*
	(0.022)	(0.024)	(0.021)	(0.023)
Women, Rel. employment (SS IV + demogr. IV)	0.079***	0.072***	0.074***	0.067***
	(0.023)	(0.024)	(0.022)	(0.022)
Pooled, Rel. employment (SS IV + demogr. IV)	0.065***	0.060***	0.064***	0.058***
	(0.021)	(0.021)	(0.019)	(0.020)
F-stat (rows 1-3)	24.90	11.40	35.41	13.79
Panel B: Labor supply estimates (2000-2023)				
Men, Imm. employment (SS IV)	0.052***	0.047***	0.038***	0.029***
	(0.006)	(0.005)	(0.007)	(0.007)
Women, Imm. employment (SS IV)	0.062***	0.038***	0.114***	0.049**
	(0.017)	(0.012)	(0.036)	(0.021)
Pooled, Imm. employment (SS IV)	0.053***	0.041***	0.065***	0.036***
	(0.009)	(0.008)	(0.016)	(0.011)
F-stat (rows 4-6)	53.35	102.27	47.88	88.41
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 the pooled sample) is regressed on (log) relative employment, instrumented with the imputed relative population, which is constructed as 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. First-stage F statistics are reported. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

become smaller and more college-intensive during the post-2000 period.

As for the other estimates in Table 6, the crowding-in effects on the employment-population ratio are more similar across education groups, ranging around 0.04-0.06. For the specification using full-time workers only, the complementarity coefficients on less educated are a bit smaller than those in columns (1) and (2), but coefficients for the employment-population ratio are larger for all groups. This suggests that the labor supply effects of immigrants may have been stronger in pushing natives towards full-time employment, as immigrants filled the more temporary positions.

The refinements and extensions of the Ottaviano and Peri (2012) estimates discussed in this section have confirmed a crucial feature of the productive interactions between

Table 6: 2SLS estimates by education

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Elasticity estimates (2000-2023)				
Pooled, Rel. employment - No HS diploma	0.111***	0.090***	0.027	0.038*
	(0.029)	(0.025)	(0.036)	(0.021)
Pooled, Rel. employment - HS diploma	0.017***	0.014***	0.020***	0.018***
	(0.005)	(0.004)	(0.004)	(0.003)
Pooled, Rel. employment - Some college	0.039***	0.038***	0.045***	0.044***
	(0.004)	(0.003)	(0.004)	(0.003)
Pooled, Rel. employment - College degree	0.111***	0.101***	0.121***	0.111***
	(0.008)	(0.006)	(0.008)	(0.006)
Panel B: Labor supply estimates (2000-2023)				
Pooled, Imm. employment - No HS diploma	0.032	0.038**	0.126**	0.139***
	(0.019)	(0.019)	(0.054)	(0.033)
Pooled, Imm. employment - HS diploma	0.045**	0.052***	0.142***	0.155***
	(0.020)	(0.019)	(0.055)	(0.033)
Pooled, Imm. employment - Some college	0.049**	0.056***	0.146***	0.160***
	(0.020)	(0.020)	(0.055)	(0.033)
Pooled, Imm. employment - College degree	0.051***	0.058***	0.147***	0.160***
	(0.019)	(0.019)	(0.052)	(0.031)
Weights	Yes	No	Yes	No
Experience FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No

Notes: This table reports 2SLS estimates for the 2000-2023 period. In each panel, each set of 4 column-specific coefficients pertains to a separate regression that includes 4 endogenous variables and 4 instruments. In Panel A, the outcome variable is the pooled (log) relative weekly wage, while the endogenous variables are the interactions of (log) relative employment with 4 education dummies (no high school diploma, high school diploma, some college education, college degree or more). These are instrumented using the interactions 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 variables are the interactions of (log) immigrant employment with 4 education dummies (no high school diploma, high school diploma, some college education, college degree or more). These are instrumented using the interactions 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). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

immigrants and natives in the long run and added three new insights. First, even when these two groups have similar education and age, they show a significant degree of complementarity, implying that they do not compete for the same jobs, but rather that the employment of one group enhances the relative productivity of the other. This was the core message of Ottaviano and Peri (2012) and is confirmed, expanded, and substantially strengthened in this analysis. Second, these complementarities are particularly strong for workers with no high school degree, and even stronger for workers with college degrees or more. Since the latter group was also the fastest-growing group of immigrants in the last 20 years, it is unsurprising that the average complementarity between immigrants and natives appears to have increased post-2000. Third, these complementarities are accompanied by an additional effect on natives, attracting them into the labor market, suggesting that the presence of immigrants may shift natives towards jobs that they also prefer for their non-wage attributes. As we have shown, the employment-population ratio of natives has responded positively to immigrant inflows in the last 20 years. More immigrants in similar skill groups may increase the willingness of natives to supply labor if they believe they will be more likely to find a desirable and fulfilling job, as we will argue in the next section. Overall, these complementarities and crowding-in effects are significant and seem to have grown stronger over the last two decades.

6 Effects on occupational specialization and upgrading

What mechanisms contributed to generating the complementarity and positive employment effects of immigration on natives of similar education and experience? One natural candidate is occupational specialization based on comparative advantage and relative preferences (as modeled in D'Amuri and Peri (2014)). Occupational separation between natives and immigrants has been identified in local economies by several studies (e.g., Peri and Sparber (2009, 2011b); Cattaneo, Fiorio, and Peri (2015)), and occupational upgrading by 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. Additionally, if immigration increases the probability of finding a job closely matched to natives' communication and cognitive preferences, it may raise their willingness to supply labor and to search for jobs. Hence, a positive employment effect can be driven by such a mechanism.

To investigate these mechanisms in our setting, we proceed in two steps. First, we ask whether natives moved away from manual-intensive and toward more communication-intensive occupations in response to immigration. Second, we assess whether this shift may have moved the occupational distribution of natives toward occupations that pay higher wages and that may also be more desirable to natives along other dimensions, in order to test whether these potential occupational changes implied an increase in native wages and greater willingness to work.

We begin by using O*NET data to measure tasks performed across occupations. We evaluate whether, holding tasks fixed in each occupation as of 2000, natives moved to more communication-intensive and less manual-intensive occupations in each cell in response to immigration (i.e., the ratio between communication and manual tasks increased).[26] As described in Section 2, we construct measures of "occupational importance of tasks" by associating each occupation with the average indices for manual and communication tasks performed by workers in 2000. We then weight these occupational indices by the share of native hours worked in each occupation, within each education k-experience j cell in each considered year t, obtaining the cell-specific native supply of manual and communication tasks. In line with the model presented in Peri and Sparber (2009), we run the following regression:

$$\ln(Rel\ Task\ Index_D)_{kjt} = \phi_{kj} + \phi_t + \beta_{task} \ln\left(\frac{Empl_{Fkjt}}{Empl_{Dkjt}}\right) + e_{kjt} \tag{16}$$

where $(Rel\ Task\ Index_D)_{kjt}$ is equal to the cell-specific ratio between occupation-based communication and manual task intensities. Native specialization along the lines of comparative advantages (communication for natives, manual tasks for immigrants) in response to a greater inflow of immigrants implies an increase in the relative task supply measure.

Table 7 reports the 2SLS estimates of coefficient β_{task} from equation (16), following the same structure and specifications as the previous IV regression tables. The coefficients are positive and statistically significant for all samples (men, women, pooled) and specifications, and are also remarkably similar across periods (1980-2019 and 2000-2023). Consistent with the idea that increased immigration pushed natives into occupations where communication-related tasks are more important relative to manual tasks, we find that a 1% increase in immigrant relative employment within a skill cell increased native relative task supply in that cell by 0.12% to 0.21% in the 2000-2023 period (0.08 to 0.19% in 1980-2019). An increase in the relative supply of communication-to-manual tasks will be associated with higher wages (if communication tasks are better compensated) and with higher native labor supply (if natives prefer communication-intensive work to manual tasks as a job amenity as well).

Next, we ask whether immigration shifted the cell-specific occupational distribution for natives toward occupations that pay relatively higher wages. As described in Section

[26] Importantly, our results might underestimate the impact of immigration if immigrants also contribute to changing the task content of occupations over time. Our strategy only captures changes in native task performance due to reallocation across occupations.

2, we construct a measure of "occupational wage" by associating each occupation with the average national weekly wage paid to workers in 1980. We then 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 toward occupations with higher weekly wages (i.e., occupational upgrading) over time implies an increase in this "occupational quality" measure. In Table 8, we report the 2SLS estimates of coefficient β_{occ} from the following regression:

$$\ln(Occ\ Index_D)_{kjt} = \phi_{kj} + \phi_t + \beta_{occ} \ln\left(\frac{Empl_{Fkjt}}{Empl_{Dkjt}}\right) + e_{kjt} \tag{17}$$

where $(Occ\ Index_D)_{kjt}$, as described, is equal to $\sum_{Occ}\Big((Share_{occ})_{Dkjt} x (Wage_{occ})_{Dkj,1980}\Big)$, the employment share-weighted occupation wage in 1980 for domestic workers with 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 toward higher-paying occupations (based on 1980 wage data).

Table 8 presents the estimates of coefficient β_{occ} from equation (17). The coefficients are positive and mostly significant for men and the pooled sample in the 1980-2019 period, consistent with the idea that immigration pushed natives into higher-paid occupations. However, they are negative for women. In the more recent period (2000-2023), the pooled estimates show a positive significant effect, while the effects for men and women individually are positive but not significant. Considering the pooled estimates, an increase of immigrants resulting in a 10 log points increase in relative employment within a skill cell (about 10%) increased the occupational quality (wage) of natives in that cell by 0.15 to 0.24% using the 1980-2019 estimates, or by 0.17 to 0.23% using the more recent period.

The reallocation dynamics found in this section are broadly consistent with our previous estimates of increased labor participation among natives and positive complementarity effects. Immigration appears to push natives toward more communication-intensive jobs where they are more productive and supply more labor. This evidence rationalizes previous findings by showing that immigration pushed natives to specialize in tasks that are comple-

Table 7: 2SLS estimates on task supply of natives

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
	Panel A: Relative task supply estimates (1980-2019)			
Men, Rel. employment (SS IV + demogr. IV)	0.192***	0.161***	0.164***	0.138***
	(0.041)	(0.042)	(0.035)	(0.037)
Women, Rel. employment (SS IV + demogr. IV)	0.102***	0.130***	0.087**	0.119***
	(0.034)	(0.031)	(0.036)	(0.034)
Pooled, Rel. employment (SS IV + demogr. IV)	0.109***	0.105***	0.087***	0.088***
	(0.024)	(0.026)	(0.023)	(0.025)
F-stat (rows 1-3)	71.58	75.80	92.05	96.08
	Panel B: Relative task supply estimates (2000-2023)			
Men, Rel. employment (SS IV + demogr. IV)	0.168***	0.206***	0.157***	0.195***
	(0.032)	(0.051)	(0.026)	(0.043)
Women, Rel. employment (SS IV + demogr. IV)	0.153***	0.214***	0.143***	0.203***
	(0.039)	(0.057)	(0.035)	(0.049)
Pooled, Rel. employment (SS IV + demogr. IV)	0.132***	0.181***	0.122***	0.172***
	(0.033)	(0.049)	(0.028)	(0.042)
F-stat (rows 4-6)	24.90	11.40	35.41	13.79
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Panel A considers the 1980-2019 period, while Panel B considers the 2000-2023 period. Both panels report 2SLS estimates from regressions where the outcome variable is a measure of natives' task supply in log (for men, women, or the pooled sample, depending on the row), capturing the cell-specific ratio between occupation-based communication and manual task intensities. We regress this variable on (log) relative employment, instrumented with the imputed relative population, which is constructed as 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). First-stage F statistics are reported. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024. O*NET version 7.0 database downloaded on 05/23/2024.

mentary to those performed by immigrants and where natives have a comparative advantage (i.e., language). This specialization resulted in both higher wages for natives, and increased labor supply as well, as natives appear to prefer these communication-intensive occupations.

7 Simulated effects of immigration on native wages and employment rates: 2000-2023

In this section, we return to the model described in Section 3. Using the parameter $1/(\sigma_N)$, newly estimated in the 2000-2023 sample with more current econometric methods, in combination with standard elasticity parameters from the literature (including Ottaviano and Peri (2012), Card and Lemieux (2001), Goldin and Katz (2009) and Autor et al. (2020)), we estimate the effects of changes in immigrant supply in each skill group occurred in the

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, Rel. employment (SS IV + demogr. IV)	0.001	0.004	0.014**	0.014**
	(0.009)	(0.008)	(0.006)	(0.005)
Women, Rel. employment (SS IV + demogr. IV)	-0.035**	-0.033***	-0.026**	-0.027***
	(0.014)	(0.012)	(0.011)	(0.010)
Pooled, Rel. employment (SS IV + demogr. IV)	0.015*	0.015***	0.026***	0.024***
	(0.007)	(0.006)	(0.004)	(0.004)
F-stat (rows 1-3)	71.58	75.80	92.05	96.08
Panel B: Occupational quality estimates (2000-2023)				
Men, Rel. employment (SS IV + demogr. IV)	-0.003	-0.008	0.003	0.001
	(0.010)	(0.014)	(0.007)	(0.009)
Women, Rel. employment (SS IV + demogr. IV)	0.017	0.015	0.022**	0.026
	(0.011)	(0.015)	(0.011)	(0.016)
Pooled, Rel. employment (SS IV + demogr. IV)	0.022***	0.017*	0.023***	0.022***
	(0.007)	(0.009)	(0.007)	(0.008)
F-stat (rows 4-6)	24.90	11.40	35.41	13.79
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Panel A considers the 1980-2019 period, while Panel B considers the 2000-2023 period. Both panels report 2SLS estimates from regressions where the outcome variable is a measure of natives' occupational quality in log (for men, women, or the pooled sample, depending on the row), capturing the cell-specific employment-weighted occupation wage in 1980. We regress this variable on (log) relative employment, instrumented with the imputed relative population, which is constructed as 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). First-stage F statistics are reported. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

2000-2023 period on native wages by skill group. Our approach proceeds in two steps. First, we equate the marginal productivity of each type of workers to their wages, obtaining a wage equation for each type of native worker (denoted as usual by D) of education group k and experience j. Then, we take the 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 we obtain is equation (21), shown in Appendix D. Using the estimated elasticity values, wage bill shares for each skill group, and percentage changes in the supply of foreign-born in each skill group, we can then calculate the effects of the change in immigrant supply from 2000 to 2023 on native wages of each group.

We present wage results grouped by native workers' education level (with responses averaged across age groups). The results of these simulations are shown in columns (1) to (4) of Table 9. Differences across the simulations in columns (1) to (4) reflect varying choices of elasticity parameters, which are taken from their estimated values. The specific values used in each simulation are reported in the bottom six rows of the table. In column (1), the choice of parameter values for the simulation follows the preferred specification of Ottaviano and Peri (2012) for parameters not specific to immigrant-native interactions. 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 set equal to 0.065 for all groups, reflecting our pooled sample estimate from Table 5 using weights (the estimate in the third row of column (1) in Panel A). In column (2), we leave the set of non-immigration related parameter values unchanged, but we allow $1/(\sigma_N)$ to differ between more and less educated individuals, using $1/(\sigma_N)_L = 0.042$ for those with a high school degree or less (the average of our estimated coefficients in the first two rows of Panel A in Table 6), and $1/(\sigma_N)_H = 0.076$ for those with some college education or more (the average of the estimates in the last two rows of Panel A in Table 6). This choice reflects evidence from our previous sections showing that complementarity between immigrants and natives appears stronger among college-educated workers than among other groups.

We test the robustness of our results to alternative parameter configurations. In column (3), we increase the complementarity between broad education groups and set $1/\sigma_{H-L} = 0.61$, the exact estimate from Goldin and Katz (2009). In column (4), we use $1/\sigma_{EDU,H} = 1/\sigma_{EDU,L} = 0$, implying perfect substitution within broad education groups. The standard errors for the $1/(\sigma_N)$ parameters are taken from Tables 5 and 6, while other elasticity values are from the same sources as the estimated parameter.

Using these parametrizations, we proceed as follows. We begin by generating 1,000 extractions from a joint normal distribution for a given configuration of the parameters. Then, using formula (21) from Appendix D, we calculate the wage effect for each education-experience group in response to the same immigration inflow for 2000-2023 and compute the mean and standard deviation of the 1,000 simulated values. Native wage changes for each education group and the overall average (along with their standard errors), reported in columns (1) to (4) of Table 9, are obtained by averaging wage changes of each education-experience group, weighted by each group's beginning-of-period wage bill share in the relevant education group or overall.[27]

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 2000-2023 helped the wage growth of less educated natives (those with high school degree or less) by between 2.6% and 3.4%. This represents a significant boost in real wages, especially considering that the real wage growth of this group during the 2000-2023 period was actually negative, at around -5%.[28] Second, in spite of the large inflow of college-educated immigrants, the complementarity between immigrants and natives, especially when capturing 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, these groups experienced small or negligible effects (between -0.7% and +0.5%), mostly not statistically significant if we account for the simulated standard errors. Third, the average effect on native wages was small, overall positive (+0.6% to +0.7%), and not statistically significant when accounting for simulated standard errors. 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 3%, versus 0-1% as found in that previous analysis) and are similar for college graduates (with effects close to 0).

Column (5) of Table 9 shows the effects of immigration on native employment-population ratios, calculated using the supply responses estimated previously. Specifically, we multiply the cell-specific percentage change in immigrant employment (approximated by the log difference in log immigrant employment) between 2000 and 2023 by the β_{emp} estimates from Table 6 for the corresponding education group. We use the set of four education-specific estimates for the sample of all workers (column (2) in Panel B of Table 6). We then aggregate results by education group and overall, weighting by cell native employment at the beginning of the period of interest (i.e., 2000 for Table 9).

These simulated values reveal two additional potential effects of immigration. First,

[27] We report the wage effects on foreign-born in the Online Appendix.

[28] See Table 10.

during the 2000-2023 period, immigration boosted the employment-population ratio of natives on average by 2.6 percentage points (with particularly large effects for college graduates, who experienced an increase of 4.9 p.p.). This employment effect suggests that wage complementarity and occupational upgrading drew more natives into employment. Second, the effect varies by education level, with the strongest positive effects for more educated natives. The group of least educated, instead, experienced a small decrease in the employment-population ratio. This is because in the least educated group, *a decline* in the supply of immigrants took place over the 2000-2023 period, which reduced the labor supply of natives as well. On the other hand, estimates in column (5) show that the groups of native workers with high school degrees, some college education and college degree, all experienced increases in their employment-population ratios (between 1.8 and 4.9 p.p.) due to positive immigration flows.

The positive effect on the employment-population ratio of natives reveals an additional effect of immigrants on employment of natives not studied in the original factor-supply approach. The wage effects, on the other hand, account for complementarity across skill cells as generated by our model in Section 3. Our results are inconsistent with either strong wage competition effects or crowding out of natives from the labor market. Instead, they support significant complementarity between immigrants and natives and a positive effect on native labor force participation.

8 Conclusions

In this paper, we have extended and updated a framework that has been broadly used since the 2000s to enrich our understanding of the recent national effects of immigration on US wages and employment. This framework, developed in Borjas (2003), Ottaviano and Peri (2012), and Manacorda et al. (2012), has had a significant influence on research and policy discussions. By differentiating the impact of immigrants on native wages 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.

This paper updates the estimates of the key parameters that capture productive complementarity between natives and immigrants across skill groups by using more recent data

Table 9: Calculated effect on native wages and employment-population ratio, as response to change in immigrant labor supply 2000-2023

	Percentage change in native wages				Percentage change in native supply
	(1)	(2)	(3)	(4)	(5)
Group:					
No High School Degree	2.8	2.8	3.2	2.6	-1.5
	(1.0)	(0.9)	(1.0)	(0.9)	
High School Degree	3.2	3.1	3.4	3.1	2.9
	(0.4)	(0.4)	(0.4)	(0.4)	
Some College Education	0.5	0.5	0.4	-0.7	1.8
	(0.7)	(0.7)	(0.7)	(0.2)	
College Degree	-0.7	-0.5	-0.6	0.3	4.9
	(0.6)	(0.5)	(0.5)	(0.3)	
Average	0.6	0.7	0.7	0.7	2.6
	(0.6)	(0.6)	(0.6)	(0.3)	
Parameter configuration:					
$1/\sigma_{H-L}$	0.54	0.54	0.61	0.54	
	(0.06)	(0.06)	(0.065)	(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)	
$1/(\sigma_N)_H$	0.065	0.076	0.076	0.076	
	(0.021)	(0.005)	(0.005)	(0.005)	
$1/(\sigma_N)_L$	0.065	0.042	0.042	0.042	
	(0.021)	(0.016)	(0.016)	(0.016)	

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 (21) from Appendix D. 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 beginning-of-period 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. Column (5) reports 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 6, 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.

and applying a modern set of rigorous econometric techniques. Additionally, relative to the approach of the 2010s, we explicitly model and estimate potential supply responses to immigration that affect natives' employment-to-population ratios.

Our estimates establish that immigrants have a substantial degree of productive complementarity with natives. This offsets the competition effect, resulting in increases in both native wages and employment-to-population ratios for most native workers in response to immigrant inflows. We also show that immigrant inflows after 2000 became increasingly concentrated among college-educated workers, and that these immigrants exhibited strong complementarity with both skilled and unskilled natives, particularly boosting wages for less educated American workers. Additionally, we show that one plausible mechanism through which immigration results in a positive complementarity and a wage boost for natives is through natives' specialization along the lines of comparative advantage. We find that an increase in immigration prompts natives to specialize in occupations that are relatively more communication-intensive than manual, resulting in higher wages. The positive labor-supply effect on natives and their shift towards communication-intensive jobs is consistent with the concept that those occupations may be preferred by natives also for their amenity attributes at given wages.

Finally, applying our improved estimates to simulate immigration effects over the past 23 years yields clear evidence of wage gains for less educated natives, with no signs of employment displacement for most native workers. This paper, by focusing on national effects rather than the local effects considered in most recent studies, provides a complementary and important picture of the recent effects of immigrants in the US labor markets.

Appendix

A Additional evidence

Table 10: Immigration and changes in native wages by education-experience groups, 2000–2023

Education (1)	Experience (2)	2000-2023 percentage change in employment due to new immigrants (%) (3)	2000-2023 percentage change in native weekly wages (%) (4)
No High School Degree	1 to 5 years	-12.7	-7.2
	6 to 10 years	-26.2	-4.2
	11 to 15 years	-23.9	-5.3
	16 to 20 years	-13.6	-8.4
	21 to 25 years	-0.1	-3.5
	26 to 30 years	11.2	-4.5
	31 to 35 years	23.3	-3.5
	36 to 40 years	31.1	-5.0
	All Experience Groups	-4.4	-4.9
High School Degree	1 to 5 years	1.4	-10.7
	6 to 10 years	1.6	-9.9
	11 to 15 years	2.7	-11.3
	16 to 20 years	5.2	-7.9
	21 to 25 years	7.1	-6.6
	26 to 30 years	10.8	-4.2
	31 to 35 years	14.8	-3.8
	36 to 40 years	18.9	-6.8
	All Experience Groups	7.2	-10.3
Low Education	**All Experience Groups**	3.3	-8.1
Some College Education	1 to 5 years	-0.3	-11.3
	6 to 10 years	-0.1	-12.2
	11 to 15 years	1.2	-13.1
	16 to 20 years	1.8	-9.8
	21 to 25 years	3.5	-9.3
	26 to 30 years	6.2	-7.0
	31 to 35 years	10.8	-9.3
	36 to 40 years	18.7	-10.3
	All Experience Groups	3.8	-9.9
College Degree	1 to 5 years	7.3	-3.7
	6 to 10 years	12.1	-5.8
	11 to 15 years	16.7	-8.1
	16 to 20 years	18.0	-6.7
	21 to 25 years	17.6	-2.0
	26 to 30 years	18.4	-1.2
	31 to 35 years	25.3	-4.8
	36 to 40 years	39.3	-4.2
	All Experience Groups	17.2	-5.1
High Education	**All Experience Groups**	10.1	-0.5

Notes: This table extends Ottaviano and Peri (2012)'s Table 1 to the 2000-2023 period. For the 32 education-experience cells, the table reports the percentage change, between 2000 and 2023, in 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 native hours worked.
Source: ACS and Decennial Census data downloaded from IPUMS on 01/12/2024.

B Robustness

Table 11: Bootstrap methods for main results (2000-2023)

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Wild cluster bootstrap P-values for Elasticity estimates (2000-2023)				
Men, Rel. employment (SS IV + demogr. IV)				
t-based, Rademacher	0.036	0.058	0.023	0.057
t-based, Webb	0.032	0.051	0.020	0.051
AR test, Rademacher	0.066	0.113	0.044	0.100
Women, Rel. employment (SS IV + demogr. IV)				
t-based, Rademacher	0.002	0.006	0.004	0.008
t-based, Webb	0.003	0.007	0.003	0.006
AR test, Rademacher	0.015	0.047	0.017	0.058
Pooled, Rel. employment (SS IV + demogr. IV)				
t-based, Rademacher	0.004	0.003	0.003	0.003
t-based, Webb	0.004	0.004	0.004	0.004
AR test, Rademacher	0.015	0.021	0.012	0.013
Panel B: Wild cluster bootstrap P-values for Labor supply estimates (2000-2023)				
Men, Imm. employment (SS IV)				
t-based, Rademacher	0.000	0.000	0.000	0.001
t-based, Webb	0.000	0.000	0.000	0.002
AR test, Rademacher	0.000	0.000	0.000	0.000
Women, Imm. employment (SS IV)				
t-based, Rademacher	0.011	0.004	0.031	0.031
t-based, Webb	0.009	0.004	0.027	0.030
AR test, Rademacher	0.000	0.032	0.011	0.083
Pooled, Imm. employment (SS IV)				
t-based, Rademacher	0.001	0.001	0.007	0.007
t-based, Webb	0.001	0.001	0.006	0.005
AR test, Rademacher	0.000	0.000	0.000	0.011
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table reports three p-values for each estimate of Table 5, obtained by adopting three different bootstrap methods. The first two are based on a wild cluster bootstrap procedure that applies standard Rademacher weights or Webb weights to the residuals. The last one is from a wild bootstrap of the Anderson-Rubin test, using Rademacher weights. In all cases, we perform 9,999 bootstrap replications.

Table 12: Leave-one-out shift share IV: Main estimates (2000-2023)

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Elasticity estimates (2000-2023), Pooled sample				
Mexico out, Rel. employment (SS IV + demogr. IV)	0.066***	0.063**	0.065***	0.060**
	(0.023)	(0.028)	(0.021)	(0.025)
Cuba out, Rel. employment (SS IV + demogr. IV)	0.064***	0.060***	0.064***	0.057***
	(0.021)	(0.021)	(0.019)	(0.020)
China out, Rel. employment (SS IV + demogr. IV)	0.066***	0.061***	0.066***	0.059***
	(0.020)	(0.021)	(0.019)	(0.020)
Philippines out, Rel. employment (SS IV + demogr. IV)	0.065***	0.061***	0.065***	0.058***
	(0.021)	(0.021)	(0.019)	(0.020)
Korea out, Rel. employment (SS IV + demogr. IV)	0.066***	0.061***	0.065***	0.058***
	(0.021)	(0.021)	(0.019)	(0.020)
Panel B: Labor supply estimates (2000-2023), Pooled sample				
Mexico out, Imm. employment (SS IV)	0.069***	0.062***	0.101***	0.079***
	(0.015)	(0.012)	(0.021)	(0.018)
Cuba out, Imm. employment (SS IV)	0.054***	0.041***	0.066***	0.036***
	(0.009)	(0.008)	(0.017)	(0.011)
China out, Imm. employment (SS IV)	0.053***	0.040***	0.062***	0.034***
	(0.009)	(0.008)	(0.016)	(0.010)
Philippines out, Imm. employment (SS IV)	0.053***	0.041***	0.064***	0.035***
	(0.009)	(0.008)	(0.016)	(0.010)
Korea out, Imm. employment (SS IV)	0.053***	0.041***	0.064***	0.035***
	(0.009)	(0.008)	(0.016)	(0.010)
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table reports 2SLS estimates that replicate the analysis in Table 5, but using a leave-one-out version for the immigrants' shift-share IV (pooled sample only). One of the five major countries is excluded in turn (Mexico, Cuba, China, the Philippines, Korea). Panel A reports 2SLS estimates of the immigrant-native elasticity of substitution, using relative weekly wage in log as the outcome. Panel B reports 2SLS estimates for native labor supply, using native employment-population ratio as the outcome. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.

Table 13: Alternative construction of shift-share IV: 1960-1970 flows

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Elasticity estimates (2000-2023)				
Men, Rel. employment (SS IV + demogr. IV)	0.048**	0.044*	0.052**	0.043*
	(0.022)	(0.025)	(0.021)	(0.024)
Women, Rel. employment (SS IV + demogr. IV)	0.082***	0.075***	0.076***	0.069***
	(0.023)	(0.025)	(0.022)	(0.023)
Pooled, Rel. employment (SS IV + demogr. IV)	0.067***	0.062***	0.066***	0.059***
	(0.021)	(0.022)	(0.019)	(0.020)
F-stat (rows 1-3)	24.03	11.39	34.14	13.82
Panel B: Labor supply estimates (2000-2023)				
Men, Imm. employment (SS IV)	0.055***	0.049***	0.036***	0.028***
	(0.006)	(0.005)	(0.008)	(0.008)
Women, Imm. employment (SS IV)	0.065***	0.040***	0.119***	0.050**
	(0.017)	(0.012)	(0.038)	(0.021)
Pooled, Imm. employment (SS IV)	0.057***	0.044***	0.068***	0.036***
	(0.010)	(0.008)	(0.017)	(0.011)
F-stat (rows 4-6)	43.07	72.79	37.46	65.30
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table reports 2SLS estimates that replicate the analysis in Table 5, but using flows from 1960 to 1970 to construct the 'shares' part of the immigrants' shift-share IV. Panel A reports 2SLS estimates of the immigrant-native elasticity of substitution, using relative weekly wage in log as the outcome. Panel B reports 2SLS estimates for native labor supply, using native employment-population ratio as the outcome. First-stage F statistics are reported. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.

C Alternative supply specifications

We explore a few alternative specifications for the labor supply estimates. Specifically, we run the following regressions:

$$\ln\left(Empl_{Dkjt}\right)=\phi_{kj}+\phi_{t}+\beta_{emp}\ln\left(Empl_{Fkjt}\right)+e_{kjt} \tag{18}$$

$$\frac{Empl_{Dkjt}}{Pop_{Dkjt}}=\phi_{kj}+\phi_{t}+\beta_{emp}\ln\left(\frac{Pop_{Fkjt}}{Pop_{Fkj\bar{t}}+Pop_{Dkj\bar{t}}}\right)+e_{kjt} \tag{19}$$

$$\frac{Empl_{Dkjt}}{Pop_{Dkjt}}=\phi_{kj}+\phi_{t}+\beta_{emp}\ln\left(\frac{Pop_{Fkjt}}{Pop_{Fkjt}+Pop_{Dkj\bar{t}}}\right)+e_{kjt} \tag{20}$$

using the shift-share IV for immigrants to instrument the main regressor throughout. In equations (19) and (20), the main regressor is the (log of) foreign-born share of total population. In the former, we fix the whole denominator at the beginning of the analysis period (either 1980 or 2000), while in the latter we fix only the native population in the denominator at the beginning of the period ($\bar{t}$). Results are reported in Table 14 for the 1980-2019 period and in Table 15 for the 2000-2023 period. In both tables, Panel A estimates equation (18), Panel B estimates equation (19), and Panel C estimates equation (20).

Table 14: Alternative specifications for labor supply estimates (1980-2019)

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Log native employment on Log immigrant employment				
Men, Immigrant SS IV	0.337**	0.297*	0.444***	0.356**
	(0.137)	(0.165)	(0.165)	(0.168)
Women, Immigrant SS IV	1.061***	0.689**	1.522***	0.818**
	(0.324)	(0.293)	(0.429)	(0.344)
Pooled, Immigrant SS IV	0.670***	0.475**	0.867***	0.532**
	(0.202)	(0.207)	(0.249)	(0.218)
F-stat (rows 1-3)	16.19	18.48	15.86	18.38
Panel B: Native emp-pop ratio on Log foreign share of population				
Men, Immigrant SS IV	0.094***	0.078***	0.144***	0.085***
	(0.025)	(0.023)	(0.039)	(0.033)
Women, Immigrant SS IV	0.059**	0.030	0.204***	0.097**
	(0.023)	(0.020)	(0.069)	(0.048)
Pooled, Immigrant SS IV	0.052***	0.038**	0.109***	0.056**
	(0.018)	(0.017)	(0.037)	(0.025)
F-stat (rows 4-6)	21.08	23.85	18.00	23.85
Panel C: Native emp-pop ratio on Log foreign share of population				
Men, Immigrant SS IV	0.136***	0.098**	0.228**	0.107**
	(0.049)	(0.038)	(0.089)	(0.050)
Women, Immigrant SS IV	0.086**	0.037	0.322**	0.122*
	(0.041)	(0.029)	(0.145)	(0.071)
Pooled, Immigrant SS IV	0.076**	0.048*	0.171**	0.071*
	(0.032)	(0.026)	(0.077)	(0.038)
F-stat (rows 7-9)	11.01	16.56	9.15	16.56
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table reports 2SLS estimates for alternative labor supply specifications for the 1980-2019 period. Panel A estimates equation (18), Panel B estimates equation (19), and Panel C estimates equation (20). We use the our shift-share IV for immigrants to instrument the main regressor (log of immigrant employment in Panel A, and log of immigrant share of total population in Panels B and C, fixing different terms at their value at the beginning of the period). First-stage F statistics are reported. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.

Table 15: Alternative specifications for labor supply estimates (2000-2023)

Specification	(1)	(2)	(3)	(4)
Sample	All workers		Full-time workers only	
Panel A: Log native employment on Log immigrant employment				
Men, Immigrant SS IV	0.462***	0.408***	0.499***	0.408***
	(0.087)	(0.051)	(0.107)	(0.051)
Women, Immigrant SS IV	0.724***	0.528***	0.917***	0.540***
	(0.150)	(0.101)	(0.206)	(0.121)
Pooled, Immigrant SS IV	0.588***	0.465***	0.686***	0.471***
	(0.111)	(0.072)	(0.143)	(0.077)
F-stat (rows 1-3)	53.35	102.27	47.88	88.41
Panel B: Native emp-pop ratio on Log foreign share of population				
Men, Immigrant SS IV	0.052***	0.048***	0.039***	0.030***
	(0.006)	(0.006)	(0.007)	(0.007)
Women, Immigrant SS IV	0.062***	0.038***	0.115***	0.051**
	(0.016)	(0.013)	(0.036)	(0.022)
Pooled, Immigrant SS IV	0.054***	0.042***	0.065***	0.037***
	(0.009)	(0.009)	(0.016)	(0.011)
F-stat (rows 4-6)	65.28	143.19	51.56	143.19
Panel C: Native emp-pop ratio on Log foreign share of population				
Men, Immigrant SS IV	0.070***	0.060***	0.055***	0.038***
	(0.010)	(0.008)	(0.012)	(0.010)
Women, Immigrant SS IV	0.084***	0.048***	0.163**	0.064**
	(0.027)	(0.017)	(0.063)	(0.029)
Pooled, Immigrant SS IV	0.072***	0.052***	0.093***	0.046***
	(0.016)	(0.012)	(0.030)	(0.015)
F-stat (rows 7-9)	26.23	73.71	18.23	73.71
Weights	Yes	No	Yes	No
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table reports 2SLS estimates for alternative labor supply specifications for the 2000-2023 period. Panel A estimates equation (18), Panel B estimates equation (19), and Panel C estimates equation (20). We use the our shift-share IV for immigrants to instrument the main regressor (log of immigrant employment in Panel A, and log of immigrant share of total population in Panels B and C, fixing different terms at their value at the beginning of the period). First-stage F statistics are reported. Cells are weighted by employment. Robust standard errors are clustered at the cell level (education by experience). Significance levels: *** for p<0.01, ** for p<0.05, * for p<0.1.

D Formula for the wage effect of all immigrants on native wages

Let ΔL_{Fkj} denote the change in foreign-born supply in education k-experience j group between two periods, and let L_{Fkj} denote the initial value of supply of immigrants in that group. 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:

$$\begin{aligned}\left(\frac{\Delta w_{Dkj}}{w_{Dkj}}\right)^{Total} &= \frac{1}{\sigma_{HL}}\sum_{H,L}\sum_{l}\sum_{i}\left(s_{Fli}\frac{\Delta L_{Fli}}{L_{Fli}}\right) \\ &+\left(\frac{1}{\sigma_l}-\frac{1}{\sigma_{HL}}\right)\sum_{l}\sum_{i}\left(s_{Fli}^{HH,LL}\frac{\Delta L_{Fli}}{L_{Fli}}\right) \\ &+\left(\frac{1}{\sigma_{EXP}}-\frac{1}{\sigma_k}\right)\sum_{i}\left(s_{Fki}^{k}\frac{\Delta L_{Fki}}{L_{Fki}}\right) \\ &+\left(\frac{1}{\sigma_N}-\frac{1}{\sigma_{EXP}}\right)\left(s_{Fkj}^{kj}\frac{\Delta L_{Fkj}}{L_{Fkj}}\right)\end{aligned} \tag{21}$$

In equation (21) the terms s_{Fkj} represent the share of wages accruing to foreign-born workers F of education k and experience j, within the group defined by the superscript. Hence, for instance, s_{Fkj}^{kj} denotes 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 and L are the broadest aggregates of workers with high school diploma or less and with some college education or more, respectively. Equation (21) is the formula we use in Section 7 to obtain the total wage effects of immigration for each group of native workers.

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