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Who competes with whom? Using occupation characteristics to estimate the impact of immigration on native wages

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ABSTRACT

Many studies have examined the impact of immigration on native wages. Some of these studies have relied upon education-experience groups to define labor markets and identify the wage elasticity with respect to immigrant labor supply. However, evidence suggests that immigrants' educational attainment is treated differently in the labor market and constructing labor markets based upon this characteristic leads to potentially biased conclusions. We utilize O*NET occupational characteristics to form a different set of labor markets. Our analysis finds higher partial equilibrium effects on native wages than prior work using education-experience skill groups, as expected. These larger effects, however, are shown to be concentrated on the least skilled natives. Estimates of the total wage effect along the distribution of occupational skills confirm that the negative wage effect is concentrated on native workers in the bottom tail of the distribution. Natives in the upper tail of the distribution experience wage gains as a result of immigration. The distributional impact is likely due to the distribution of skills among recent immigrants.

1. Introduction

A simple labor market model of supply and demand implies that immigration to a local labor market will result in falling wages, *ceteris paribus*. Examining the implications of immigration on local labor markets has been an important topic in recent years, both within the economic literature and in the popular press. However, as recent surveys suggest (Kerr and Kerr, 2011; Dustmann, Schönberg, and Stuhler, 2016), the results are far from uniform. A difficulty in estimating the impact of immigration on earnings is identifying and isolating labor markets. It has become standard in one strand of the literature to analyze the impact of immigration on groups of similarly skilled native workers as defined by education and work experience. This approach, pioneered by Borjas (2003), implicitly assumes that these education-experience groups identify labor markets in which immigrants and natives are perfect substitutes. However, the assumption of perfect substitutability has been challenged, and estimates suggest that a degree of *imperfect* substitutability exists between immigrants and natives within these education-experience groups (Card, 2009; Ottaviano and Peri, 2012; Dustmann and Preston, 2012; Dustmann, Frattini, and Preston, 2012; Manacorda, Manning, and Wadsworth, 2012). As pointed out by Ottaviano and Peri (2012), this fact is nontrivial. If immigrants and natives are imperfect substitutes, then any wage effect of immigration would be concentrated on existing immigrants, not natives.

The result that education is an imperfect proxy for overall skill level, and especially so for immigrants, is well-documented in the literature. First, there is significant wage dispersion *within* education groups (Murnane, Willett, and Levy, 1995; Ingram and Neumann, 2006). This suggests that skills other than educational attainment are being rewarded in the labor market. Second, immigrants earn less than similarly educated natives (Bratsberg and Terrell, 2002; Bratsberg and Ragan, 2002; Ferrer and Riddell, 2008). This fact has been attributed to differing employment distributions across occupations and a lower return to education for immigrant workers. Several scenarios exist for the above differentials in returns to education. First, there may be more uncertainty about the quality of education received by immigrants abroad, leading employers to hedge against the possibility that the immigrant's education is lower quality. Second, language barriers limit the value of similarly educated immigrants. Third, immigrants face differential returns to education due to downgrading upon arrival in the US (Dustmann, Schönberg, and Stuhler, 2016; Friedberg, 2000; Mattoo Neagu, and Özden, 2008; Neagu, 2009; Sharpe, 2015). Sharpe (2015) uses O*NET data for the required level of education needed to adequately perform a job and finds that immigrants are twice as likely to be overeducated as natives for the positions they hold. The difference in over-education rates increases with the amount of schooling and is most profound for highly educated, newly arrived immigrants. We do not investigate these causes, but rather note that

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immigrants enter the US and are pushed toward jobs in which they possess too much education compared to the average worker.

Prior studies have used several methods to account for the imperfect substitutability between immigrants and natives. Some have turned to estimating the elasticity of substitution between immigrants and natives and simulating the total wage effect of immigration on native wages (Mancorda, Manning, and Wadsworth, 2012; Ottaviano and Peri, 2012; Peri and Sparber, 2009; among others). The validity of this approach, however, has been questioned, as the estimated elasticities of substitution are not robust to changes in key assumptions (Borjas, Grogger, and Hanson, 2012). Llull (2018b) improves upon this framework by allowing imperfect substitutability to enter endogenously into a structural model of the labor market that flexibly defines labor market competition based on “skill units” and occupation. Others have moved away from the education-experience group analysis altogether and analyzed varying definitions of skill groups: based on the native wage distribution (Dustmann, Frattini, and Preston, 2012) and occupation groups (Camarota, 1997; Card, 2001; Orrenius and Zavodny, 2007; Steinhardt, 2011). Other studies have focused on specific industries (Bratsberg and Raaum, 2012) or used natural experiments where immigrants were exogenously allocated (Friedberg, 2001; Glitz, 2012). Dustmann and Glitz (2015) examine firm level adjustments, including factor utilization and firm level decisions to enter or exit. Friedberg (2001) uses occupation prior to immigration as an instrument, an approach we consider below.

We propose that stratifying the labor market by occupation rather than education results in an improved measure of labor market competition. Existing studies incorporating occupations as a proxy for skill are relatively sparse. Camarota (1997) uses one CPS cross-section to estimate the impact of immigration on wages within occupations and finds that a 1% increase in immigration will decrease the wages of the average native worker by 0.5%. However, the use of a single cross-section and small within-occupation sample size makes causal inference difficult. Card (2001) estimates city-specific impacts of immigration on occupational wages for 175 cities using 1990 US Census data and finds that the immigration inflows of the 1980’s decreased wages in low-skilled occupations in high-immigration cities by no more than 3%. Orrenius and Zavodny (2007) use CPS data from 1994–2000 and INS immigration data to estimate the impact of immigration on native wages in three broad occupation categories. The authors estimate that the change in immigrants over the data period decreased wages in low-skilled, manual occupations by 0.8% and had no impact for medium-skilled and high-skilled occupations. In the case of the German labor market, Steinhardt (2011) shows that the relative wage effect of immigration on native wages is larger when stratifying the labor market by occupation compared to stratifying the labor market by education. Specifically, when stratifying by occupation, the results imply a statistically significant wage elasticity of -0.134. When stratifying by education, however, the resulting estimates are statistically insignificant.

To improve upon the studies using skill group methodology, we propose constructing labor markets by using occupation groups with similar *skill* requirements along with experience. Whereas prior skill group studies using occupations have relied on broad Census-defined occupation groups, we construct occupation groups using skill data from the O*NET. The use of O*NET data enables us to construct occupation groups with a greater degree of homogeneity in overall skill level, regardless of nationality and citizenship status, than those using either education groups or broad occupation classifications. Section 2 presents the details of our data and the methodology used to construct occupation-experience groups.

Our primary result, presented in Section 3, incorporates our occupation classification to estimate the impact of immigrants on wages in the national labor market. This approach is compared to estimates obtained by Borjas (2003). As expected if grouping workers by occupational characteristics is an improvement in constructing labor markets, we find that the partial equilibrium effect of immigration on native wages is 4 -5 times larger than the effect estimated utilizing markets defined by education group. This result is robust to several different definitions of occupation groups defined on the basis of occupational skill.

Two potential concerns arise from the initial analysis. First, stratifying labor markets by occupations may introduce bias, as occupational choice is potentially endogenous. Second, the national labor market approach identifies the partial equilibrium effect of immigration on native wages: the effect of immigration on the wages of experienced native workers relative to inexperienced native workers in the same occupation (or education) group (Dustmann, Schönberg, and Stuhler, 2016).

We address the endogeneity concern in two approaches. First, in Section 3, we use a shift share instrument, similar to Llull (2018a) and others, as one specification of our main model. For our second approach, we estimate competition intensity for the usual education-experience groups by using demographic data to identify native workers who are comparable to immigrants. We then estimate the impact in each of these competition groups. In both exercises, the estimates are similar or larger than our initial estimates, further supporting the importance of constructing appropriate labor market groups.

In Section 4, we use our occupation classification to estimate the total wage effect of immigration along the distribution of occupational skills (Dustmann, Frattini, and Preston, 2012). This approach addresses the second concern, as it provides estimates over the distribution, allowing for significant heterogeneity. Additionally, this section adds to the literature which has shown that the effect of immigration on natives is concentrated on the least-skilled native workers who are most substitutable to immigrant labor. While the estimated wage effect is not statistically distinguishable from zero in the middle of the skill distribution, we estimate large and statistically significant effects in each tail of the distribution. Specifically, we estimate a wage elasticity of -0.5 in the bottom tail where natives are substitutable to immigrant labor and a wage elasticity of roughly 0.3-0.8 in the upper tail where natives are complementary to immigrant labor.

2. Data

We draw from several data sources in this paper. The primary data are labor supply and wage data deriving from the 1960, 1970, 1980, 1990, and 2000 Public Use Micro Samples (PUMS) of the U.S. Census, and the 2009, 2010, and 2011 Public Use American Community Survey (ACS). The ACS data are pooled together to form a single 2010 cross-section. Following the work of Borjas (2003), we restrict our sample to noninstitutionalized men, aged 18-64, who earned positive wage income. A full description of both the employment and wage samples can be found in the Data Appendix.

For the main analysis reported in Section 3, we construct skill groups based on potential experience and occupation (see below for detailed discussion of these occupation groups) or based on potential experience and education, as has previously been done. As is customary in this literature, we calculate potential experience based on educational attainment. It is assumed that workers with less than a high school diploma enter the labor market at 17 years old, workers with a high school diploma or GED enter the labor market at 19, workers with some college enter the labor market at 21, and those with a college degree enter the labor market at 23. Following Borjas (2003), we limit the sample to men who have 1-40 years of potential experience and group workers into 5-year potential experience groups (i.e. 1-5 years of potential experience, 6-10 years, etc.). We construct weekly earnings by dividing annual earnings by weeks worked.

Our main data are then skill group averages of wages and hours worked. In each year, we construct the average wage of four occupation groups (or more in robustness checks) across eight experience groups. Thus, each year in our panel has 32 observations. Using the six decennial years (1960-2010), we arrive at 192 total observations for our main analysis sample.

Immigrants are identified through the survey question which asks the citizenship status of each individual. Immigrants are considered those who are either naturalized citizens or not a citizen, which should include both legal and illegal immigrants. The survey also asks all individuals who were foreign born the year they entered the United States, which allows us to identify recent immigrants for analysis.

2.1. Occupation groups

In order to form groups of workers who are similar in skill, we use the O*NET survey (version 18), which provides data on worker abilities and tasks. The O*NET survey is collected from workers across nearly 1000 occupations and is designed to provide information to both employers and workers (as well as researchers) on occupational characteristics. Following Peri and Sparber (2009, 2011), we assume that occupations are distinguished by two occupation-specific indices of task intensity: manual task intensity and communicative task intensity. Individual occupations are then grouped based on their relative communicative-to-manual task intensity.

Peri and Sparber (2009) focused on one domain of the O*NET data: abilities. We make use of four domains: abilities, knowledge, skills, and work activities. Appendix Table A1 presents a list of the variables from O*NET used in our analysis, grouped by these domains. The ability domain describes enduring attributes of the individual worker that influence job performance. For example, the verbal ability attribute describes the application of verbal information in problem solving.[1] The knowledge domain provides information about organized sets of principles and facts held by the worker. For example, knowledge of the English Language includes understanding the meaning and spelling of words, rules of composition, and grammar. The skills domain provides information about specific developed capacities that facilitate learning of new material. For example, reading comprehension is the understanding of written sentences and paragraphs in work related documents. Work activities are specific activities performed in a particular job. For example, handling and moving objects describes the physical moving of objects as a part of the daily work activities and requirements (descriptions derive from, "O*NET Content Model", 2018). We group the individual attributes in each domain into those pertaining to communication tasks and those pertaining to manual tasks as described in appendix Table A1.

Because our primary Census (and ACS) data span 1960–2010 and Census occupation definitions change over time, we use a modified occupation classification developed by Autor and Dorn (2013) (AD classification, hereafter) to create a consistent, balanced panel of occupations across all years in both the Census data and the O*NET data.

We construct two indices for each occupation: communication task intensity and manual task intensity. Our two indices are a function of two scores for each attribute provided in the O*NET data: a score for importance (I) with a range of 0-5 and a score for level (L) with a range of 0-7 for each occupation. To understand the difference between importance and level, consider the written expression ability for college professors and paralegals. Written expression is relatively important in both occupations (both receive an importance score of 4); however, the *level* of written expression needed varies significantly between these two occupations, with college professors requiring a significantly higher level (5.12) relative to paralegals (3.75). Thus, for each occupation (j) and each attribute (k), we have a level score $L_{j,k}$ and an importance score $I_{j,k}$. Grouping the attributes by communications attributes and manual attributes (as in Appendix Table A1) we calculate the mean importance score and mean level score: $\bar{I}_j^{comm}$, $\bar{L}_j^{comm}$, $\bar{I}_j^{man}$, and $\bar{L}_j^{man}$. Next, we generate manual (TS_j^{manual}) and communicative (TS_j^{comm}) task-intensity scores by multiplying the importance score and the level score. For each occupation, we then create what we call the skill ratio of communicative task intensity to manual task intensity ($\frac{TS_j^{comm}}{TS_j^{manual}}$), which is the basis for defining our occupation groups.

We construct several occupation classifications based on the distribution of our skill ratio across occupations. Our preferred specification makes use of a 4-group occupation classification (quartile, hereafter) in order to have the same number of skill groups as Borjas (2003) and others. In this literature, labor markets are defined via four broad education groups: high school dropouts, high school graduates, some college, and college graduates. Clearly, one would expect that a finer classification of skills might result in a more homogeneous market group definition (we find evidence for this in Section 3). We keep the same number of skill groups as in work by Borjas (2003) to examine the effect of changing the definition of skill groups rather than the number. In Section 3, we examine how finer skill groups can impact the results and note that it is less important than the change in definition.

Fig. 1 illustrates the evolution of immigrant labor supply shocks over time for different skill groups between 1960 and 2010. Each panel within Fig. 1 corresponds to an individual occupation group from the quartile classification described above. Recall, these occupations are derived from our ratio of communicative-to-manual task intensity. Panel A presents data for occupations in the lowest quartile of communicative-to-manual task intensity, primarily blue-collar manual-labor occupations.[2] As we progress through Panels B–D, the communicative-to-manual task intensity index is increasing.

The immigrant share is quite consistent across occupation groups (panels). In 1960, immigrant share was low for less experienced skill groups, but high for groups with more experience. Immigrant share was similar across experience groups in 1970–1990. Beginning in 2000, we see an increase in immigrant share for all skill and experience groups. In 2000, immigrant share was most concentrated in skill groups with potential experience less than 15 years. There is one notable difference across the four panels: immigrants comprise a significantly larger share of workers in manual task-intensive occupations (Panel A) and particularly within younger skill groups. In Panel A, immigrants made up 20–30% of the overall labor supply for workers with less than 20 years of experience. While younger workers appear to compete the most with immigrants regardless of occupation group, immigrants comprise only 10–15% of inexperienced workers in communicative task-intensive occupations (Panel D).

To see the relationship between wages and the occupation classification described above, Fig. 2 plots average log weekly native wages against immigrant labor supply share within occupation-experience cells (net of year, occupation group, and potential experience fixed effects). The raw data show a clear negative relationship between native wages and immigrant share: a one percentage point increase in the share of immigrants in a skill group is associated with a 1.27 percentage point decrease in native wages (standard error of 0.195).

The motivation for the occupation classification system described above is that by defining labor markets on the basis of occupational skill, we create more homogenous markets for which natives and immigrants are more perfectly substitutable. As noted in Dustmann, Schoenberg and Stuhler (2016), results using the skill-cell approach can be sensitive to the definition of skill groups if the supply elasticities differ across groups. We follow the existing literature (Borjas, Grogger, and Hanson, 2012; Ottaviano and Peri, 2012) and estimate the inverse elasticity of substitution between immigrants and native born by regressing log relative wages of immigrants and natives within a given skill group on the log relative supply of immigrant and native labor, skill group fixed effects, and year fixed effects. In Table 1, we report estimates for

[1] Bratsberg et al. (2019) uses a language requirement associated with occupations as an instrument.

[2] Table A2 of the Appendix provides a snapshot of the occupations at different points along the distribution of communicative-to-manual task intensity. Specifically, Table A2 presents the ten occupations with the highest task intensity, the ten occupations with the lowest task intensity, and the ten occupations in the middle of the distribution.

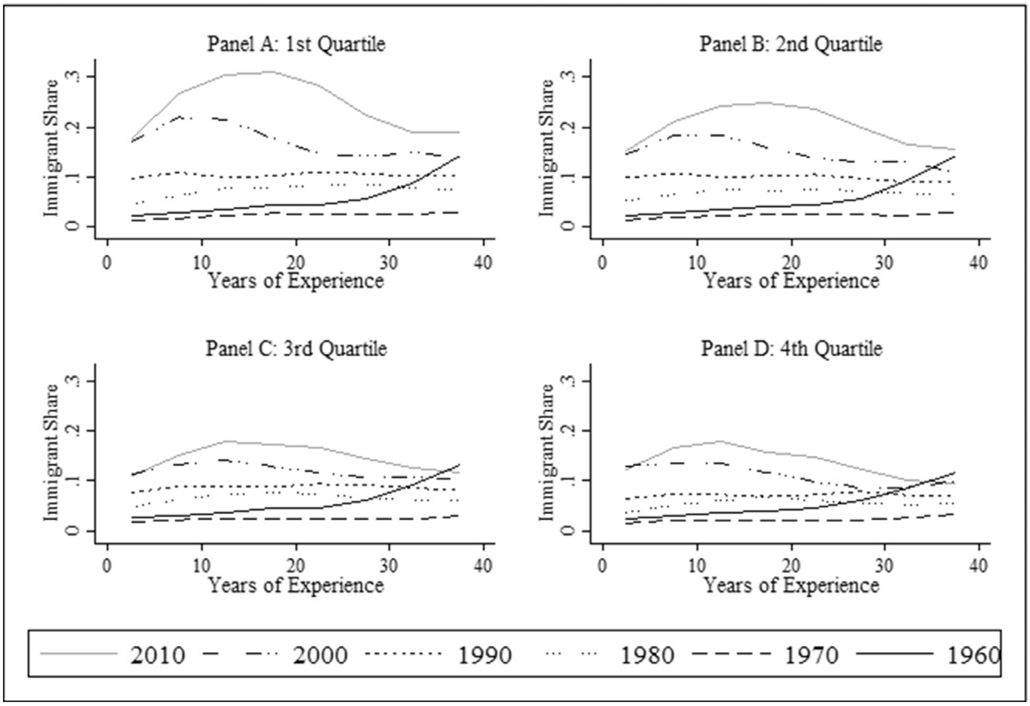

Fig. 1. Immigrant Share Over Time. Notes: Each panel presents the average immigrant labor share across potential experience groups in the corresponding quartile of the communicative-to-manual skill task ratio. Data derive from the 1960 through 2010 decennial census and ONET. We use the midpoint of each potential experience group to illustrate the trends in immigrant shares across groups.

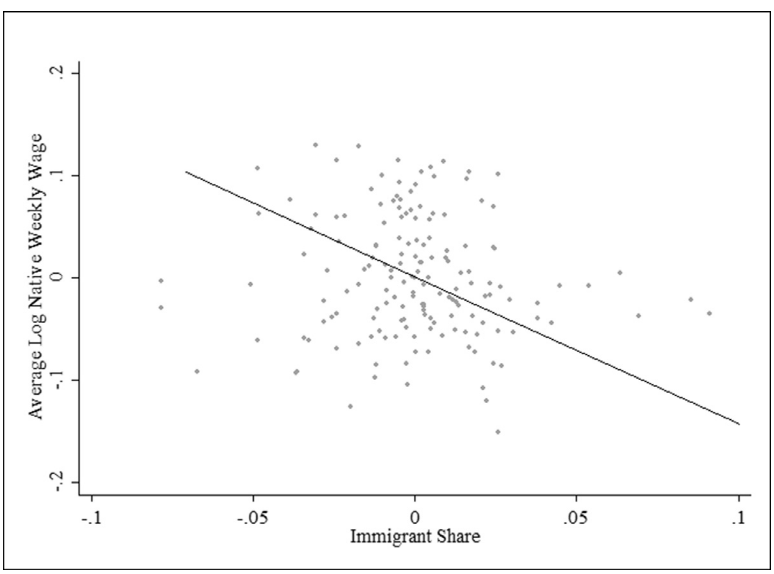

Fig. 2. Relating Wage to Immigrant Share, 1960-2010. Notes: The figure plots average log weekly native wages against immigrant labor supply within skill group (occupation-experience) cells. Log wages and immigrant share are net of year, occupation group, and potential experience group fixed effects. Data derive from 1960-2010 decennial census combined into 192 year/skill group cells. A one percentage point increase in the share of immigrants is associated with a 1.27 percentage point decrease in native wages (standard error of 0.195).

three definitions of skill groups: education-experience (column 1), AD occupation-experience (column 2) [3], and our quartile occupation and experience (column 3).

Row 1 presents estimates for the main sample that includes all noninstitutionalized male workers aged 18–64. Consistent with Ottaviano and Peri (2012), the results suggest a degree of imperfect substitutability between immigrants and natives within education-experience skill groups with an implied elasticity of substitution of 35. A similar result of imperfect substitutability (implied elasticity of 37) is present when defining labor markets using the AD occupation classification system. With our occupation classification, however, the results suggest immigrants and natives are significantly more substitutable. The coefficient of interest is statistically indistinguishable from zero and implies an elasticity of substitution of 101. In row 2, we restrict the analysis to full-time workers and the same general pattern emerges.

To see the ways in which the AD measure differs from our own, Fig. A1 of the Appendix plots the share of total hours worked along the communicative-to-manual skill ratio within AD occupation groups. Panels A and B of Fig. A1 are communicative task-intensive white-collar jobs while panels C–F are manual task-intensive blue-collar jobs. Though

[3] The occupation groups are as follows: 1) Management/Professional/Technical/Financial/Public Security, 2) Administrative Support and Retail Sales, 3) Low-Skill Services, 4) Precision Production and Craft Occupations, 5) Machine Operators, Assemblers, and Inspectors, and 6) Transportation/Construction/Mechanics/Mining/Agricultural.

Table 1
Elasticity of substitution within skill groups.

VARIABLES	(1) Educ-Exp Groups	(2) Occ-Exp (AD) Groups	(3) Occ-Exp (Quartile) Groups
All	-0.0286**	-0.0270	-0.0099
	(0.0119)	(0.0309)	(0.0354)
Full-Time Only	-0.0356***	-0.0286	-0.0168
	(0.0111)	(0.0283)	(0.0338)
Excluding Newly Arriving Immigrants	-0.0217**	-0.0668***	-0.0285
	(0.0103)	(0.0180)	(0.0230)
Education/Occupation Skill Groups	4	4	4
Experience Skill Groups	8	8	8
Total Skill Groups	32	32	32
Resulting Observations	192	192	192

1. Each cell presents the estimated inverse elasticity of substitution between immigrants and natives within a given skill group from a unique regression. We regress log relative wages of immigrants and natives within a skill group on the log relative supply of immigrant and native labor, skill group dummies, and year dummies.
2. Columns vary by definition of skill group: education-experience (column 1), AD occupation-experience (column 2), our occupation-experience (column 3). Rows vary by the sample used when constructing the dependent variable: all male workers (row 1), full-time male workers (row 2), and all male workers when newly arriving immigrants (years in US less than 10 years) are excluded (row 3).
3. All regressions are weighted using the correct weight as defined by Borjas, Grogger, and Hanson (2012). Robust standard errors clustered by skill group are reported in parentheses: *p<.01****, *p<.05***, *p<.1**.

labor supply is skewed in the expected direction for each occupation group (white-collar occupations are skewed toward relatively more communicative skills and vice versa), the variance is quite high. Because of this variability, it is reasonable to assume that, similar to skill groups defined by educational attainment, not all workers will directly compete in the labor market.

One potential limitation to the above methodology is the inclusion of recently arriving immigrants when constructing the relative wage measure. Ruist (2013) suggests that changing immigrant composition can lead to a negative correlation between immigration and native wages that may be mechanical. Specifically, including recent immigrants in the sample may confound the results if variation in immigrant wages by the number of years since arrival to the US is due to factors other than the substitutability of labor. As outlined in Section 1, the evidence of immigrant downgrading upon arrival is quite clear in the literature. Thus, in row 3, we follow Ruist (2013) and report estimates when the relative wage is constructed using a sample that excludes recent immigrants (defined as those who have resided in the US for 10 years or less). When recent immigrants are removed, the estimates are more consistent between our groups and the traditional education/experience groups. This highlights how market groups based on educational attainment may not be ideal for comparing immigrants and native born, as we further investigate in Section 3. We note that an important aspect of investigating immigrants' impacts on wages is taking into account the flow of new immigrants, thus excluding them from the analysis below would create different biases.

3. National labor market approach

To be responsive to existing literature, we begin by following Borjas et al. (1997) and Borjas (2003) and treat the U.S. as one national labor market. This approach has the advantage over the spatial correlations approach, as immigration to local labor markets is likely endogenous. This endogeneity may take several forms. Immigrants may choose to locate in high-wage cities, natives may respond to immigrant inflows by relocating, or firms may reallocate capital to high-immigrant cities in order to take advantage of the abundance of cheaper labor. To alleviate this concern, Borjas et al. (1997) suggested that the analysis should use national-level data and treat the entire US as one labor market.

The empirical model is a reduced form wage equation which links wages of native workers to the share of immigrants in their corresponding skill group. It is similar to equations estimated by Borjas (2003) and Card (2001) and controls for group-specific productivity by a collection of fixed effects. The skill-cell approach outlined in Eq. (1) identifies the relative wage effect of immigration on native wages *within* a given occupation-experience group. This estimate ignores possible cross-group complementarities and the imperfect adjustment of capital (Dustmann, Schönberg, and Stuhler, 2016; Llull, 2018b). We return to this point in Section 4.

$$w_{ijt} = \beta s_{ijt} + \theta_i + \varphi_j + \tau_t + \left(\theta_i * \tau_t\right) + \left(\varphi_j * \tau_t\right) + \left(\theta_i * \varphi_j\right) + \varepsilon_{ijt}. \quad (1)$$

Here, w_{ijt} is the mean of the log weekly wage of natives in occupation group i and experience group j at time t. s_{ijt} is the share of immigrants in occupation group i, experience group j at time t, making β the coefficient of interest. The share of immigrants in a skill group (i,j) is represented as the percent of total hours worked by immigrants. The remaining controls are vectors of linear fixed effects for occupation group (θ_i), experience group (φ_j), and year (τ_t) to control for differences in average wages across occupation groups, experience groups, and over time. The interaction of occupation fixed effects with time ($\theta_i{}^*\tau_t$) and experience-group fixed effects with time ($\varphi_j{}^*\tau_t$) control for the changing impact of occupation or experience on average wages. Lastly, the interaction of occupation fixed effects and experience group fixed effects ($\theta_i{}^*\varphi_j$) controls for any differences in the impact of experience on average wages across occupation groups. Thus, the impact of immigration on native wages is identified by variation in immigrant shares within occupation-groups and experience-groups over time.

Eq. (1) is estimated via OLS and the estimated coefficients of interest are reported in Table 2. Each column/row of Table 2 represents a different specification of Eq. (1). The columns differ by skill group classification (i.e. Education-Experience, Occupation (4 group)-Experience, etc.). Panel A reports our preferred specification where the regression is weighted by the number of observations used to calculate the average wage within a cell. We also present several robustness checks. Panels B and C present the same regression as in A, with different weighting choices. Panel D presents estimates when we include native labor force as an explanatory variable. Panel E reports estimates where the dependent variable is the mean of *residualized* log wage in each cell (Card, 2001; Jaeger, Ruist and Stuhler, 2018). Panel F reports estimates for a that includes only women. In each panel, we also report the corresponding elasticities from the estimated coefficients in brackets.[4]

[4] The share of immigrants within a skill group (s_{ijt}) in Eq. (1) is not in log form. As such, we calculated the corresponding elasticities as in Borjas (2003).

Table 2
Estimated effects of immigration on native wages.

VARIABLES	(1) Educ-Exp Groups w_{ijt}	(2) Occ-Exp Groups w_{ijt}	(3) Occ-Exp (AD) Groups w_{ijt}
Panel A: Weighted Regressions			
β coefficient on s_{ijt}	-0.162	-1.001***	-0.340**
	(0.101)	(0.217)	(0.166)
	[-0.119]	[-0.735]	[-0.250]
Panel B: Unweighted Regressions			
β coefficient on s_{ijt}	-0.256***	-0.977***	-0.513**
	(0.091)	(0.222)	(0.201)
	[-0.188]	[-0.717]	[-0.377]
Panel C: Alternative Weights (SHW)			
β coefficient on s_{ijt}	-0.221***	-0.979***	-0.489**
	(0.091)	(0.221)	(0.204)
	[-0.162]	[-0.720]	[-0.359]
Panel D: Includes Native Labor Force			
β coefficient on s_{ijt}	-0.184*	-0.905***	-0.411**
	(0.110)	(0.238)	(0.205)
	[-0.135]	[-0.664]	[-0.302]
Panel E: Residualized Log Wages, Weighted			
β coefficient on s_{ijt}	-0.134	-0.604***	-0.223*
	(0.108)	(0.201)	(0.132)
	[-0.099]	[-0.443]	[-0.164]
Panel F: Sample Includes Women			
β coefficient on s_{ijt}	-0.010	-0.537**	-0.032
	(0.111)	(0.253)	(0.194)
	[-0.007]	[-0.394]	[-0.023]
Education/Occupation Skill Groups	4	4	4
Experience Skill Groups	8	8	8
Total Skill Groups	32	32	32
Resulting Observations	192	192	192

1. Each panel represents a unique specification. For all specifications, the sample is limited to only men with 1–40 years of potential experience, and the dependent variable is the mean of log native weekly wages in a given cell, unless otherwise noted. We report estimates using the education-experience definition (column 1), our quartile occupation classification (column 2), and the occupation classification system used by Autor and Dorn (column 3). Robust standard errors are reported in parentheses and the estimated elasticity is reported in square brackets: *p<.01***, p<.05**, p<.1**.
2. Panel A presents the preferred estimates using the counts of native workers in each cell as weights. Panel B presents unweighted estimates, while Panel C presents estimates of a weighted regression using alternative weights as defined by Solon, Haider, and Wooldridge (2015). Panel D presents estimates from the weighted regression when native labor supply is included as a control variable. Panel E presents estimates from the weighted regression when the dependent variable is defined as the mean of log residualized wages in each cell. Panel F presents estimates from the weighted regression when the sample is restricted to only women.

We start by discussing our preferred estimates in Panel A. Column (1) reports estimates using the traditional education-experience classification found in the existing literature.[5] The baseline results are smaller than those found by Borjas (2003); however, as shown in the Data Appendix, this does not appear to be an issue with the data or methodology.[6] Focusing on the estimated elasticity in brackets, the results suggest that a 1% supply shock (an inflow of immigrants that increases total hours worked within an education-experience group by 1%) will reduce native wages by a modest 0.12%. In column (2), we present the estimates using occupation-experience groups, where occupations are defined using the communicative-to-manual task intensity ratio outlined in Section 2. When we group workers based on occupation-specific skills, the estimated impact of immigration is much larger. Again, focusing on the elasticities in brackets, the results suggest a 1% supply shock within a given occupation-experience group will decrease native wages by 0.74%. The results support the hypothesis that defining skill groups on the basis of education may attenuate the effects of immigration.

It may be reasonably questioned whether our results are driven by a careful construction of markets or by other factors associated with defining labor markets by occupational groups. To test this, we estimate the model using the occupation classification system developed by Autor and Dorn (2013). Results are reported in column (3). These occupation groups are similar to the typical occupation classifications used in the U.S. Census and are not defined based on occupation-specific skills. If the results are driven simply because we use occupations to define skill groups, we would expect the impact of immigration to be similar to column (2). When using this occupational-group classification, however, the impact of immigration lies between the values in column (1) and column (2), although is much closer to the estimate using the educational groups. Given the estimated inverse elasticities of substitution in Table 1, this result is unsurprising.

Rows B through F of Table 2 examine the impact of immigrant share on native wages using differing specifications and samples. In Panel A, we follow Borjas (2003) and others by utilizing population weights in order to address potential heteroscedasticity associated with aggregations of different population sizes (essentially a GLS approach). Solon, Haider and Wooldridge (2015) suggest that this type of weighting may not be fully efficient, as this approach fails to address the het-

[5] In this specification, we use the four-group classification described above (Less than HS, HS grad, some college, college grad).

[6] Borjas (2003) estimates a point estimate of -0.572; however, this estimate does not use data from 2010 and uses CPS data for 2000. We provide replication results and sensitivity tests in the Data Appendix. Using the methodology above and the same data described in Borjas (2003) produces very similar results. Thus, the methodology used above is consistent with the past literature.

eroscedasticity. To analyze the robustness of previous estimates, we estimate the main model under two alternative weighting schemes. First, we drop the weighting of each cell and simply use the 192 cells as single observations (Panel B). Second, we follow Solon, Haider, and Wooldridge (2015) by directly estimating the heteroscedasticity terms and using the weights implied by the resulting FGLS approach (Panel C). The differences in estimates are most profound for columns (1) and (3), while the estimates based on our preferred skill groupings are little changed. Overall, the results suggest that our preferred estimates are robust to these differences in weightings, although the differences in the estimated elasticity across skill groups are slightly lower.

In row D, we include native labor force as an explanatory variable. Since s_{ijt} is simply the immigrant share of total hours worked within a skill group, an increase in s_{ijt} could occur from either an increase in immigrant labor supply *or* a decrease in native labor supply. As such, row D estimates report the impact of s_{ijt} holding native labor supply constant. As before, the result that our preferred skill groups reveal a larger response in native wages to immigrant share is supported, although this specification has the smallest estimates for our measure and slightly larger estimates for the other types of skill groups. However, since the change in native labor force is likely endogenous, we do not prefer this specification. We include it to be comparable to other literature and to demonstrate that our approach has similar qualitative effects across different specifications.

One additional potential concern with the above results is that a model based on repeated cross-sections fails to account for selective attrition in skill groups over time. That is, if immigrant inflows affect employment decisions of natives and alter the sample of native workers observed in a given skill group, estimates from repeated cross-sections will be biased. This is particularly problematic given our data are decennial. Recent research relying on panel data to estimate the wage effect of immigration suggests the wage effect is attenuated when such compositional effects are ignored (Bratsberg and Raaum, 2012; Dustmann, Schönberg and Stuhler, 2017; Ortega and Verdugo, 2016). In an attempt to alleviate this concern, we report estimates when the dependent variable is defined as the log of *residualized* weekly wages in Panel E.[7] When using residualized wages, the estimated elasticities are lower than in panel A regardless of skill definition. Importantly, however, our preferred skill groups method continues to have the largest elasticity: a 1% supply shock within a given occupation-experience group will decrease native wages by 0.44%.

Panel F examines implications for women. Only in column (2) are the estimated responses statistically significant. While the inclusion of women leads to a lower elasticity (.394 as compared to .735), estimates based on other skill groupings would suggest that immigrants have little effect on wages of native women. Caution should be used in interpretation of these results. As is well known, potential experience is a poor measure of actual experience for women. Hence while the educational grouping may be most problematic for men, the experience grouping may be problematic for women. We do not address this in this paper.

Table 3 examines the sensitivity of our estimates in two important dimensions. First, we provide estimates using increasingly finer groupings based on our communicative-to-manual skill ratio. Secondly, we note that the immigrant share may be endogenous, even at the national level (see Llull, 2018a). To address the endogeneity, we use a shift share instrument and perform 2SLS estimation similar to that of Llull (2018a). The first column in Table 3 uses the level wages, as used in all but row E of Table 2. The second column uses the residualized wages, as used in row E of Table 2. Row A of Table 3 repeats the baseline estimates of Table 2: specifically, Row A, column (2) and Row E, column (2). Row B of Table 3 presents the unweighted estimates from Table 2 (Row B column 2) and new unweighted estimates using residualized wages. These are provided for comparisons.

In Row C through row F, we experiment with different skill groupings based on the distribution of the communicative-to-manual skills ratio. Our main specification in Table 2 (and Row A and B of Table 3) uses four groups to be comparable to the four education groups. The groups are determined by the quartiles of the overall ratio distribution. To arrive at other groupings, we use quintiles (Panel C), sextiles (Panel D), deciles (Panel E), and ventiles (Panel F). We note that some of the finer groupings result in higher elasticities than our baseline, while others result in lower elasticities. In each Panel, however, the results are economically larger than those using groups based on education (just as in Table 2). As noted in Dustmann, Schoenberg and Stuhler (2016), finding skill groupings with similar labor supply elasticities is important. The stability of

Table 3
Robustness checks.

VARIABLES	(1) w_{ijt}	(2) $\tilde{w}_{ijt}$
Panel A: Preferred		
β coefficient on s_{ijt}	-1.001***	-0.604***
Occupation Groups 4	(0.217)	(0.201)
Observations 192	[-0.735]	[-0.443]
Panel B: Unweighted		
β coefficient on s_{ijt}	-0.977***	-0.627***
Occupation Groups 4	(0.222)	(0.210)
Observations 192	[-0.717]	[-0.460]
Panel C: Quintile		
β coefficient on s_{ijt}	-0.916***	-0.589***
Occupation Groups 5	(0.264)	(0.210)
Observations 240	[-0.672]	[-0.432]
Panel D: Sextile		
β coefficient on s_{ijt}	-0.868***	-0.539***
Occupation Groups 6	(0.196)	(0.137)
Observations 288	[-0.637]	[-0.396]
Panel E: Decile		
β coefficient on s_{ijt}	-1.247***	-0.688***
Occupation Groups 10	(0.192)	(0.124)
Observations 480	[-0.915]	[-0.505]
Panel F: Ventile		
β coefficient on s_{ijt}	-0.886***	-0.491***
Occupation Groups 20	(0.139)	(0.091)
Observations 960	[-0.650]	[-0.360]
Panel G: 2SLS		
β coefficient on s_{ijt}	-0.745***	-0.646**
Occupation Groups 4	(0.200)	(0.269)
Observations 192	[-0.547]	[-0.474]
Panel H: 2SLS with Native Labor Force		
β coefficient on s_{ijt}	-0.673***	-0.620**
Occupation Groups 4	(0.200)	(0.266)
Observations 192	[-0.494]	[-0.455]

1. Each panel represents a unique specification. For all specifications, the sample is limited to only men with 1–40 years of potential experience. Eight experience groups are used to form the occupation-experience cells. We report the estimate for the coefficient of interest when the dependent variable is defined as level wages (column 1) and residualized wages (column 2). Robust standard errors are reported in parentheses and the estimated elasticity is reported in square brackets. *p<.01****, *p<.05***, *p<.1**.
2. Panel A presents the preferred estimates using the quartile occupation classification and the counts of native workers in each cell as weights. Panel B presents unweighted estimates using the quartile occupation classification. Panels C–F present weighted regressions (again, using native worker counts as weights) for several different occupation classifications: 5-group (Panel C), 6-group (Panel D), 10-group (Panel E), and 20-group (Panel F). Panels G and H report weighted 2SLS estimates using the quartile occupation classification system. Panel H includes native labor supply as a control variable.

[7] To residualize wage, we fit an OLS regression of log wages on observable individual characteristics (education, potential experience and its square, indicator variables for marital status, occupation group, full-time worker status, race, and full set of education-by-demographic interaction terms) and state fixed effects. We then construct the skill group average wage using the residuals.

our estimates across different categorizations suggests our occupation classification may be appropriate.

In Panels G and H, we return to the quartile groups, and use a shift share instrument for the ratio of immigrants to native born. Using data from the 1960 Census, we predict immigrant inflows at the national level based on country-of-origin specific historical migration patterns and the occupational distribution of newly arriving immigrants. Specifically, predicted immigrant inflows are calculated by multiplying the total number of newly arriving (lived in the US less than 10 years) immigrants from source country k at time t by the share of immigrants from source country k that were in skill group ij (occupation-experience group) in 1960. After summing up over countries k, the instrument is constructed as the predicted number of immigrants divided by the total number of workers in a given skill group at *t-10*. Panel G is most similar to panel A, while Panel H is similar to Panel C of Table 2 in that it controls for native labor supply. In both cases, our estimated elasticities remain larger in magnitude than the education skill groups used by others.

3.1. Who competes with whom?

The question of “who competes with whom?” in the labor market is the motivation for this paper. The motivation for stratifying the labor market into skill groups is to estimate the impact of immigration on the wages of demographically comparable natives. We have argued that our occupation-experience groups are an improvement over the education-experience groups in estimating the wage effect of immigration because we define skill groups for which immigrants and natives directly compete in the labor market. As was shown in Table 1, immigrants and natives with similar work experience are closer substitutes within our occupation groups than within education groups. While the above results suggest this to be the case, the potential endogeneity of occupational choice remains a concern. If immigrants choose occupations based on favorable labor market conditions, then the estimates in Tables 2 and 3 would be biased upward. However, if immigrants are systemically under-placed in the labor market and forced into lower wage jobs, then the estimates in Tables 2 and 3 would be biased downward. [8] It is the latter that influenced the use of education-experience groups in the early literature.

Another way to approach the question of “who competes with whom?” is to let the data determine which native workers are demographically comparable to immigrants. In this section, we return to the standard education-experience skill groups. The use of education-based skill groups in this section is valuable for two reasons. First, switching occupations is significantly easier than switching education groups. As discussed above, there may be doubt as to whether the estimates in the prior section result from defining more homogeneous skill groups or bias introduced by using occupations. Second, this analysis provides a test to the claim that imperfect substitutability within education groups is the primary force behind the mixed results seen in the previous literature.

To identify demographically comparable natives, we begin by modeling the relationship between observable characteristics and the nativity of the worker. We first estimate, using the same data as above, the following flexible probit model on male workers for each Census year separately:

$$\Pr\left(I_i = 1\right) = \Phi\left(\beta X_i + \gamma OCC_i + \delta GEOG_i\right). \tag{2}$$

[8] We did an informal test for endogeneity of occupational choice across skill groups. We regressed immigrant penetration in the quartile occupation-experience group (s_{ijt}) on lagged native wages (w_{ijt-10}) and the same set of fixed effects in Eq. (1). The resulting coefficient is negative (-0.079) suggesting immigrants are being pushed into occupations with lower wages; however, the coefficient is not statistically significant (p-value of 0.118). In finer occupation groups (deciles and ventiles), we do find a statistically significant negative effect. The magnitude of the coefficient, however, is quite small (-0.048 for deciles and -0.042 for ventiles).

I_i is a dummy variable equal to 1 if the worker is an immigrant; X_i is a vector of worker demographics including education, marital status, race, a quartic in potential experience, and a full set of education-by-demographic interactions; OCC_i is a vector of occupation-specific controls including AD occupation group fixed effects and the communicative-to-manual skill ratio; $GEOG_i$ is a vector of geographic location controls including metropolitan status, state fixed effects, and a state-by-metro interaction.[9] We use the estimated coefficients to predict the probability of being an immigrant for all natives in the sample. We assume that native workers who more closely resemble immigrants in the data are also more likely to compete with immigrants in the labor market.

Table 4 reports the average labor market and demographic characteristics of native workers in four quartiles that reflect the intensity with which they will compete with immigrants in the labor market (i.e. Quartile 1 are the native workers least like immigrants in the data). While hours worked, weeks worked, and the percentage of workers who are part-time are all fairly constant across quartiles, it is noteworthy that workers with fewer years of potential experience (younger workers) are more likely to compete with immigrants. Perhaps counterintuitively, average weekly wages are *higher* among natives that are *more* likely to compete with immigrants in the data. However, we note that a number of issues arise with considering these means. Immigrants are likely to sort geographically into areas with high wages, such as MSA’s. Indeed, this fact appears to dominate the means. But the question we and this literature are trying to address is not whether native workers who are in competition with immigrants have higher or lower wages than other native workers, but would workers who compete with immigrants have higher or lower wages than they would without competition. In addition, other factors work in the opposite direction: native minorities are much more likely to compete with immigrants—the proportion of white workers decreases uniformly across the quartiles. Similarly, the differences across education and occupation groups are as expected. Native workers who are more likely to compete with immigrants are those with less education and work in low-skill service occupations.

To estimate the impact of immigration on the native wages, we return to the standard education-experience groups and estimate the same reduced-form model in Eq. (1). Here, though, the dependent variable is now the average log weekly wage of demographically comparable natives in a given competition quartile within a given education-experience group. The results are presented in Table 5 below.

Column (1) of Table 5 presents the estimates for the full sample (as in Table 2). Then, in columns (2)–(5), we report the estimated impact on the wages in each intensity quartile. For example, the dependent variable in column (2) is the average log weekly wage of natives in the lowest competition intensity quartile. Recall that by modeling skill groups on the basis of education and experience, the implicit assumption is that all workers within these skill groups are perfect substitutes. In theory, we would expect the impact of immigration on the wages to be the same across all columns because all natives should compete equally with immigrants in the labor market. From the estimates in Table 5, however, we see that the theory does not hold. For those natives that least resemble immigrants in the data (column 2), the estimated effect of immigration on wages is *positive*, perhaps reflecting complementarities between those natives and immigrant labor. As the intensity of competition increases, the impact of immigration on native wages becomes more negative and statistically significant. For natives that most closely resemble immigrants in the data (Very High Competition), the effect of immigration is highly statistically significant with an implied elasticity of -0.32.

[9] We estimated the initial probit models without occupation fixed effects and the skill ratio and the results are not sensitive to their exclusion. These results are available upon request.

Table 4
Native worker characteristics by intensity of competition with immigrants (2000).

	Low Competition	Medium Competition	High Competition	Very High Competition
Observations (N)	**614,414**	**614,414**	**614,412**	**614,411**
Weekly Wage	$839.94	$869.24	$1,037.94	$870.06
Hours Worked per Week	43.87	43.76	43.93	43.12
Weeks Worked per Year	47.37	47.82	47.79	47.07
Potential Experience	19.10	19.16	18.58	17.84
White	94.76%	90.62%	89.26%	65.20%
African American	5.24%	9.38%	10.50%	12.26%
Full-Time	82.84%	84.63%	84.44%	82.16%
Live in Metropolitan Area	25.37%	67.68%	89.79%	94.39%
Education Groups				
Less Than High School	5.21%	8.35%	9.23%	13.00%
High School Graduate (or GED)	38.30%	44.69%	35.61%	48.45%
Some College	21.29%	22.72%	22.79%	26.03%
College Graduate	35.21%	24.25%	32.36%	12.52%
Occupation Groups (AD)				
Management & Professional	32.57%	32.45%	43.74%	35.69%
Administrative Support & Retail Sales	14.94%	13.74%	12.90%	12.13%
Low-Skill Services	4.67%	7.21%	8.19%	13.05%
Precision Production & Craft	5.56%	6.16%	4.47%	4.92%
Machine Operators & Assemblers	7.99%	8.93%	6.49%	6.48%
Transportation, Construction, Mining, Agricultural	34.26%	31.52%	24.22%	27.73%
Occupation Groups (Skill Based)				
Quartile 1	24.57%	24.75%	18.74%	22.07%
Quartile 2	28.60%	29.51%	24.89%	29.15%
Quartile 3	24.89%	26.69%	30.54%	30.63%
Quartile 4	21.94%	19.06%	25.83%	18.16%

1. Summary statistics derive from the 2000 wage sample for male native workers (see Data Appendix for sample restrictions).

The same general pattern is seen in columns (6) and (7). Column (6) presents results where the dependent variable is average log weekly wage of demographically comparable natives in the high and very high competition groups, while column 7 presents results for natives in the low and medium competition groups. From column (6), the wage elasticity is similar to those in Table 2 and suggests that a 1% immigration shock would decrease the wages of these natives by 0.31%. As a result, we can conclude that the results in the prior section are not the result of the endogeneity of occupational choice; rather, it is the construction of a more homogeneous group of perfectly substitutable workers that directly compete in the labor market.

Overall, these results are consistent with the previous literature in one important way. In instances where immigrants are, on average, less-skilled than natives (as is the case in the US), recent research suggests that the effect of immigration on native wages is concentrated on the least educated natives (Cortes, 2008; Ottaviano and Peri, 2012; Dustmann, Frattini, and Preston, 2012). So, while the estimated elasticity is larger (in absolute value), the results of this paper fit nicely with this interpretation. Immigrant inflows have no adverse effect on the wages for those native workers who are least similar to immigrants (columns 2, 3, and 7); however, the effect increases as the similarity between natives and immigrants increases. This may also explain how different researchers obtain different estimates. Depending on the mix of occupation and the associated skills, the estimated response when not separating by skill group would be a sample average of these coefficients.

4. Effect along the occupational skill distribution

While the national labor market approach is appealing for the reasons discussed above, past studies suggest this approach may overstate the negative effect of immigration on wages. Dustmann, Schönberg, and Stuhler (2016) suggest that the national labor market approach identifies the *relative* wage effect of immigration (within a given skill cell), not the *total* wage effect that accounts for skill complementarities. In order to provide estimates of the total effect of immigration on native wages, researchers have used an approach that relies on variation in immigrant inflows across regions (i.e. metropolitan areas, commuting zones, or states) to identify the effect on native wages.

Regardless of the definition of the labor market (i.e. local vs. national), however, empirical methods estimating the average effect likely mask significant heterogeneity along the skill distribution. If immigrants are, on average, less skilled than natives, as is the case in the US, we would expect the effect of immigration to be concentrated on the wages of the least skilled native workers. The two most salient examples in the existing literature are Altonji and Card (1991), who report a wage elasticity of -1.1 for white male high school dropouts, and Dustmann, Frattini, and Preston (2012), who find large negative effects (-0.5) at the bottom of the income distribution and large positive wage effects (0.4) near the top of the income distribution in the U.K. Given that immigrant inflows have become less skilled, on average, over time and immigrants typically downgrade upon arrival, one may also expect that the wage effect should be concentrated at the bottom tail of the occupational skill distribution. As such, in this section, we incorporate our occupation group classification into the regional approach to estimate the *total* wage effect of immigration along the occupational skill distribution.

In the spirit of Dustmann, Frattini, and Preston (2012), we estimate the total effect of immigration along the distribution of occupational skills at 10 percentage point intervals. We start by defining the occupational skill distribution based on the skill index defined in Section 2. Occupations are then placed into one of 10 groups (j) according to their position on the skill distribution (based on the 1980 Census). For example, occupations with a communicative-to-manual skill index below the 10th percentile are grouped in j=1, while occupations with a communicative-to-manual skill index above the 90th percentile are grouped in j=10. We then estimate the following regression model *separately* for each occupation group (j):

$$\Delta \log w_{jkt} = \beta_j \Delta s_{kt} + \gamma \Delta X_{jkt} + \theta_t + \Delta\epsilon_{jkt} \tag{3}$$

The dependent variable is the change in the average log wage of native workers ($\Delta\log w_{jkt}$) within occupation group (j) across local labor markets (k). The coefficient of interest (β_j) is the coefficient on changes in the immigrant share of labor (Δs_{kt}) in local labor market (k). We include local labor market-specific controls for changes in demographics (ΔX_{jkt}) and year fixed effects (θ_t). Because measurement error is a

Table 5
Immigration wage impact for demographically comparable natives.

VARIABLES	(1) All w_{ijt}	(2) Low Competition w^{Q1}_{ijt}	(3) Medium Competition w^{Q2}_{ijt}	(4) High Competition w^{Q3}_{ijt}	(5) Very High Competition w^{Q4}_{ijt}	(6) High and Very High Competition w^{Top50}_{ijt}	(7) Low and Medium Competition w^{Bot50}_{ijt}
β coefficient on S_{ijt}	-0.162	0.231	-0.165	-0.328**	-0.435***	-0.421***	0.061
	(0.101)	(0.275)	(0.159)	(0.140)	(0.154)	(0.126)	(0.185)
	[-0.126]	[0.170]	[-0.121]	[-0.241]	[-0.320]	[-0.309]	[0.045]
Observations	192	192	192	192	192	192	192
R-squared	0.999	0.998	0.998	0.998	0.998	0.999	0.999

1. Each column represents a different specification. In all columns, eight experience groups and four occupation groups are used. The dependent variable in column (1) is the mean log native wage in a given education-experience group. The dependent variables in columns (2)–(5) are the mean log wages of natives in competition intensity quartile j in each education-experience group. In column (6), the dependent variable is the mean log wages of natives in competition intensity quartiles 3 and 4 (thus, the top 50% most likely to compete with immigrants). Column (7) reports estimates for the bottom 50%. The independent variable of interest is the share of total hours worked by immigrants in each education-experience group. Robust standard errors are reported in parentheses and the estimated elasticity is reported in square brackets. *p<.01****, *p<.05***, *p<.1**.
2. All regressions are weighted. The weights are the sample size used to create the average log weekly wage in a given skill group.

concern for cells with small sample sizes, labor markets are not stratified by potential experience in this analysis.[10]

We estimate Eq. (3) using the sample of working-age noninstitutionalized male population from IPUMS data from the 1990 Census, 2000 Census, and 2010 American Community Survey. We follow the existing literature (Card, 2001; Jaeger, Ruist, and Stuhler, 2018) by constructing the dependent variable using residualized log wages.[11] ΔX_{jkt} includes controls for changes in the average age of the population and changes in the average occupational skill ratio. We also include a Bartik-style local labor demand shifter as a control variable to control for local changes in wages as predicted by lagged 2-digit industry composition (Bartik, 1991). As is common in the literature, we define local labor markets (k) as metropolitan areas (MSAs). One potential concern with this approach, however, is a lack of observations for certain MSAs. Aydemir and Borjas (2011) show that measurement error from small sample sizes leads to significant attenuation bias in the estimated effect of immigration on native wages. As such, we limit the analysis to the 150 metropolitan areas with the largest number of immigrant observations.[12]

Because the location choices of immigrants across local labor markets are endogenous, Eq. (3) is estimated via 2SLS using a variant of the shift-share instrumental variable (e.g. Altonji and Card, 1991; Card, 2001). Specifically, we predict an immigrant inflow to each metropolitan area based on historical migration patterns specific to country of origin and occupational distributions of immigrants. The idea is that while current immigrant location choices are endogenous with respect to local labor market conditions, historical migration patterns are not. This identifying assumption relies on the common result that the most important determinant of location choice is the share of the existing population that is foreign born.

Our version of the shift-share instrument follows most closely to that in Card (2001). The predicted immigrant inflows assume that each metropolitan area k will receive the same share of immigrants from country c. In this analysis, the initial shares are based on the immigrant distribution in 1980. Specifically, we predict immigrant inflows to MSA k at time t by:

$$\hat{I}_{kt} = \sum_{k=1}^{n} \sum_{c=1}^{n} \alpha_{c,k,1980} * I_{c,\,US,t}. \tag{4}$$

The first term on the right-hand side, $\alpha_{c,\,k,\,1980}$, is the share of immigrants from country c that resided in metropolitan area k in 1980. The second term, $I_{c,\,US,\,t}$, is the total number of immigrants from country c that arrived in the US in each subsequent decade (1990, 2000, and 2010). We utilize annual data from the Immigration and Naturalization Service (INS, now the Department of Homeland Security) to construct the decadal inflows of immigrants from 1980-2010 ($I_{c,\,US,\,t}$). The instrument is then constructed as the predicted number of immigrants from Eq. (4) divided by the total lagged labor force in metropolitan area k at *t-10*.

[10] The more traditional approach to estimating the total wage effect would also stratify labor markets by potential experience (as suggested by Dustmann, Schönberg, and Stuhler, 2016). We have estimated such a specification for several different subgroups of the population and report the estimates in Table A3 of the Appendix. The results complement those in the paper.

[11] To residualize wage, we fit an OLS regression of log wages on observable individual characteristics (education, potential experience and its square, indicator variables for marital status, occupation group, full-time worker status, race, and full set of education-by-demographic interaction terms) and state fixed effects. We then construct the skill group average wage using the residuals.

[12] Though not reported here, we also estimated the model using different samples of MSAs. The results are quantitatively and qualitatively similar when we restrict the analysis to the top-100 CBSAs or expand the sample to include all CBSAs (available upon request).

Table 6
Effects along the skill distribution.

VARIABLES	(1) OLS $\Delta \log \tilde{w}_{jkt}$	(2) 2SLS $\Delta \log \tilde{w}_{jkt}$	(3) First Stage Estimates ΔS_{kt} on $\hat{I}_{kt}$
10^{th} percentile β_j coefficient on ΔS_{kt}	-0.194* (0.101)	-0.550** (0.261)	0.135*** (0.022) [29.50]
20^{th} percentile β_j coefficient on ΔS_{kt}	-0.080 (0.128)	-0.366 (0.242)	0.144*** (0.019) [32.92]
30^{th} percentile β_j coefficient on ΔS_{kt}	-0.203* (0.104)	-0.595** (0.262)	0.136*** (0.022) [23.52]
40^{th} percentile β_j coefficient on ΔS_{kt}	0.069 (0.108)	-0.027 (0.272)	0.133*** (0.020) [34.95]
50^{th} percentile β_j coefficient on ΔS_{kt}	-0.049 (0.104)	-0.238 (0.183)	0.125*** (0.022) [27.40]
60^{th} percentile β_j coefficient on ΔS_{kt}	0.174 (0.122)	0.311 (0.200)	0.128*** (0.019) [29.73]
70^{th} percentile β_j coefficient on ΔS_{kt}	0.294** (0.130)	0.063 (0.265)	0.118*** (0.020) [30.73]
80^{th} percentile β_j coefficient on ΔS_{kt}	0.185 (0.119)	0.358** (0.174)	0.108*** (0.021) [27.60]
90^{th} percentile β_j coefficient on ΔS_{kt}	0.402*** (0.149)	0.425 (0.264)	0.121*** (0.022) [27.64]
100^{th} percentile β_j coefficient on ΔS_{kt}	0.581*** (0.149)	0.816* (0.435)	0.111*** (0.019) [40.07]
Sample size=300 for each row			

1. Each cell presents the estimated total wage effect at a given decile along the communicative-to-manual skill ratio. In columns (1) and (2), the dependent variable is the change in the mean log residualized wage of native men in skill group *j* in MSA *k*. Column (1) presents the OLS estimates, while column (2) presents the 2SLS estimates. The first stage estimates are reported in column (3) (first stage F-stat in square brackets). In each regression, the sample size is 300 observations (150 MSAs over two years).
2. All regressions are weighted by the sample size used to create the average log weekly wage in a given skill group at time t. Robust standard errors clustered by MSA are reported in parentheses, *p<.01****, *p<.05***, *p<.1**.

4.1. Results

The estimated total wage effect at different points of the occupational distribution are presented in Table 6. The OLS estimates are presented in column (1) and the 2SLS estimates in column (2). The coefficient estimates on $\hat{I}_{kt}$ from the first stage regressions of Δs_{kt} on $\hat{I}_{kt}$ and ΔX_{jkt} (with first stage F-stats reported in square brackets) are reported in column (3). Several interesting results emerge from Table 6. First, consistent with the existing literature and the results in Section 3.1, the effect of immigration is shown concentrated on the least skilled native workers. From the 2SLS estimates in column (2), the total wage effect is negative and statistically significant in the bottom tail of the skill distribution. The results suggest that a 1% increase in the share of immigrants to a local labor market leads to a 0.5% decrease in the wages of natives in the bottom tail of the skill distribution. While the estimates are less precise in the middle of the distribution, immigrant inflows are shown to have a significant positive effect at the upper tail of the distribution. Again, the result is consistent with the fact that, in the US, higher-skilled native workers are largely complementary to immigrant labor, while low-skilled native labor is substitutable for immigrant labor. Moreover, the magnitude of these effects mirror those of Dustmann, Frattini, and Preston (2012). Second, in comparing the OLS and 2SLS estimates, the OLS estimates are attenuated by the endogeneity of immigrant sorting across MSAs and occupations. In the bottom deciles, the larger negative results via 2SLS suggest immigrants endogenously cluster in high-wage MSAs (Sharpe, 2019).

To visualize the effects in Table 6, we also plot the 2SLS estimates in Fig. 3 below. The solid black line represents the estimates from Column (2) of Table 6, and the dashed grey lines are the 95% confidence interval. Fig. 3 tells a similar story. The negative wage effect is concentrated on the least skilled native workers employed in occupations that require relatively more manual tasks. As skill level increases, the effect of immigration on native wages disappears. While imprecisely estimated at some points, the effect is positive for natives in the upper tail of the distribution.

One may be tempted to compare the results in Table 6 to those in Tables 2 and 3. Such direct comparisons are misplaced for several reasons. First, Table 6 reports the total wage effect of immigration on native wages, whereas estimates in Section 3 are the relative wage effects. It is possible that the relative wage effect–the effect of immigration on the wages of natives within a particular skill group–would be larger (in absolute value) than the total wage effect. The total wage effect reported in this section accounts for indirect effects such as cross-skill group complementarities and the adjustment of capital (Dustmann, Schönberg and Stuhler, 2016; Llull, 2018b). Second, the results in Section 3 rely on the national labor market approach, while the results in the present

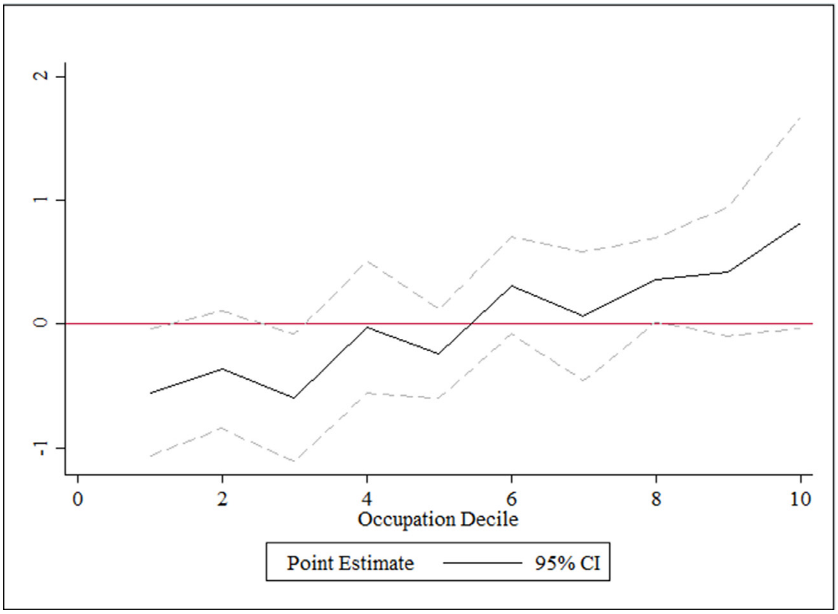

Fig. 3. 2SLS Estimates Across Occupation Deciles. Notes:Plots of coefficients from Table 6 column 2. Estimated total wage effect at a given decile along the communicative-to-manual skill ratio. Slope coefficients from 2SLS regression of change in the mean log residualized wage of native men in skill group j in MSA k. Dotted lines represent 95% confidence intervals.

section use the spatial correlations approach. Some argue that the area approach leads to attenuated estimates of the wage effect of immigration (Borjas, 2003). Third, the data differ across the two sections. In Section 3, we rely on data from 1960–2010. Due to a limited INS data time series and a first-differenced specification, we rely on data form 1990-2010 in the present section. However, these results are comparable and complimentary to those in Section 3 and provide further insight into the distributional impacts of immigration on wages.

5. Conclusion

“Who competes with whom?” is an important question when trying to uncover the impact of immigration on native wages. It is difficult to identify groups of natives and immigrants who are perfect substitutes. The prior literature has relied upon education and experience groups to estimate the effect of immigration on native wages. We argue that because of educational differences and education downgrading of immigrants, this may not be ideal. We improve upon the methodology by forming skill groups using occupation-specific skill requirements.

Using the national labor market skill-cell approach, we show that when labor markets are defined based on occupation-specific skills, the estimated (relative) impact of immigration is significantly more negative compared to defining labor markets on the basis of education. Specifically, the estimated impact of immigration on native wages is 4-5 times larger than estimates using education-experience groups. The results are robust to changes in occupation classification and suggest a 1% immigrant labor supply shock will decrease native wages by about 0.4-0.8%.

Because occupational choice is endogenous, we provide several robustness checks of the main results. Our 2SLS estimates in Section 3 are an attempt to address issues of both endogenous response by native workers who shift occupation groups and the potential that changes in capital structure may be coincident with immigration and have a similar effect. These estimates suggest that the response of native workers to shift away from skill groups most impacted by immigration imply that our main results are a net effect, including this shift. Moreover, the use of repeated cross-sections of the US Census means that compositional changes in skill groups over time could bias the results. We attempt to address this concern by using residualized log wages in Sections 3 and 4. In Section 3, the results using the residualized wages are significantly lower regardless of the definition of skill groups. Importantly, however, the relative wage effect remains largest when we use our occupation classification system compared to the more traditional education-experience skill groups. Lastly, in Section 3.1, we analyze the impact of immigration on the wages of *demographically comparable* natives *within* education-experience groups. While a bit smaller in magnitude, the results are similar to those found when using occupation-experience groups. Findings suggest a 1% immigrant labor supply shock will decrease the wages of natives most likely to compete with immigrants in the labor market by roughly 0.3-0.4%. For those least likely to compete with natives, however, the wage effect is zero.

The national labor market approach identifies the partial equilibrium effect of immigrant inflows on native wages. To be responsive to the existing literature, we estimate the total wage effect of immigrant inflows along the distribution of occupation-specific skill. The analysis yields a familiar result: the wage impact of an immigrant inflow is concentrated on the least-skilled native workers. For those in the bottom two deciles of the skill distribution, immigration has large negative effects (elasticity estimate around -0.5). As we move up the skill distribution, this effect quickly disappears. For workers in the upper tail of the distribution, the effect of immigration is positive (elasticity around 0.3 to 0.8).

Our findings highlight that estimation of the impact of immigrants on markets is sensitive to the construction of the market. Education is likely heterogeneous even within the United States, and more so when comparing immigrants, perhaps especially new immigrants. Our results also highlight that the impact of immigration is heterogeneous. Current immigrant flows appear to be competing with lower skill workers, therefore negative impacts are concentrated among lower skilled native workers. In contrast, higher skilled workers appear to benefit from immigration, perhaps due to complementarities. Our results suggest that further research into how employers value immigrants' education is important in understanding both the impact of immigrants and the experience of immigrants. Further research on interactions between capital-labor substitution and the role of immigration is clearly needed. Finally, research into how native workers respond to immigrant competition through geographic and occupation mobility is warranted.

Appendix

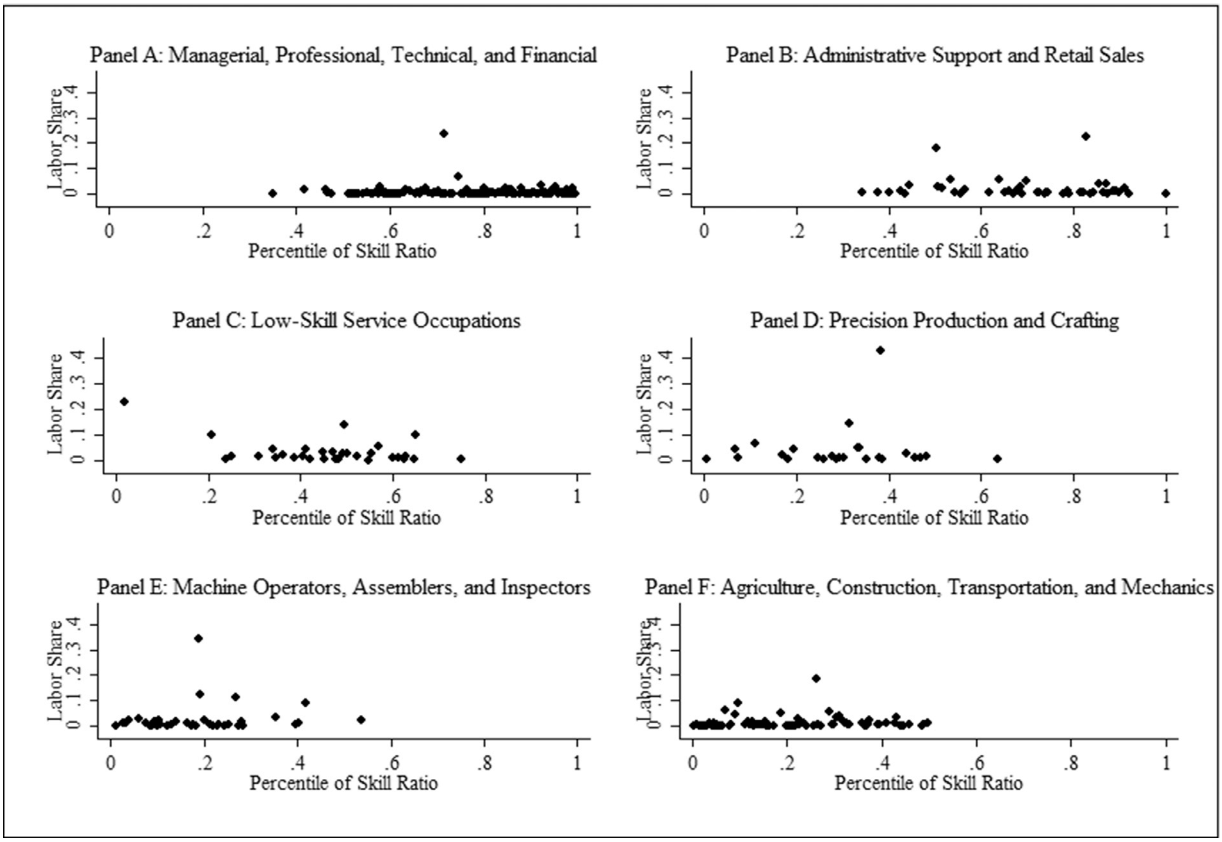

Fig. A1. Employment along communicative-to-manual skill ratio. notes: the figure plots the share of total hours worked in a given occupation against the communicative-to-manual skill intensity ratio within AD occupation groups. Each panel corresponds to one of the six Autor and Dorn occupation groups. Data derive from the 2000 census.

Table A1
O*NET elements (by domain) used in task intensity indices.

Abilities	Task Category
Oral Comprehension	Communicative
Oral Expression	Communicative
Written Comprehension	Communicative
Written Expression	Communicative
Fluency of Ideas	Communicative
Originality	Communicative
Inductive Reasoning	Communicative
Deductive Reasoning	Communicative
Perceptual Speed	Communicative
Speech Clarity	Communicative
Speech Recognition	Communicative
Speed of Limb Movement	Manual
Arm-Hand Steadiness	Manual
Response Orientation	Manual
Finger Dexterity	Manual
Multi-limb Coordination	Manual
Reaction Time	Manual
Wrist-Finger Speed	Manual
Rate Control	Manual
Control Precision	Manual
Manual Dexterity	Manual
Gross Body Coordination	Manual
Trunk Strength	Manual
Extent Flexibility	Manual
Static Strength	Manual

(*continued on next page*)

Table A1 (*continued*)

Abilities	Task Category
Dynamic Strength	Manual
Dynamic Flexibility	Manual
Stamina	Manual
Gross Body Equilibrium	Manual
Explosive Strength	Manual
Knowledge	
English Language	Communicative
Communications	Communicative
Building and Construction	Manual
Mechanical	Manual
Skills	
Reading Comprehension	Communicative
Active Listening	Communicative
Writing	Communicative
Speaking	Communicative
Installation	Manual
Operation Monitoring	Manual
Equipment Maintenance	Manual
Work Activities	
Interpreting the Meaning of Information for Others	Communicative
Communicating with Supervisors, Peers, or Subordinates	Communicative
Communicating with Persons Outside Organization	Communicative
Establishing and Maintaining Interpersonal Relationships	Communicative
Assisting and Caring for Others	Communicative
Selling or Influencing Others	Communicative
Resolving Conflicts and Negotiating with Others	Communicative
Performing for or Working Directly with the Public	Communicative
Performing General Physical Activities	Manual
Handling and Moving Objects	Manual
Controlling Machines and Processes	Manual
Operating Vehicles, Mechanized Devices, or Equipment	Manual

1. Ability Elements and Domain names taken from "O*NET Content Model", 2018.
2. Task Category determined by authors.

Table A2
Occupations by skill ratio.

Occupation Code	Comm-to-Man Skill Ratio
Panel A: Top-10 Occupations	
Proofreaders	51.07
Economists, market and survey researchers	47.10
Actuaries	41.22
Lawyers and Judges	32.30
Psychologists	31.32
Insurance Underwriters	28.64
Social Scientist and Sociologists	25.36
Financial managers	20.86
Mathematicians and Statisticians	20.69
Human Resource and labor relations managers	20.61
Panel B: Middle-10 Occupations	
Postal clerks, excluding mail carriers	1.42
Construction Inspectors	1.41
Health technologists and technicians	1.40
Cashiers	1.40
Retail Salespersons and Sales Clerks	1.34
Supervisors of food preparation and service	1.33
Farm Managers	1.26
Cooks	1.21
Personal Service Occupations, n.e.c	1.21
Supervisors of motor vehicle transportation	1.14
Panel C: Bottom-10 Occupations	
Machinery maintenance occupations	0.23
Textile sewing machine operators	0.22
Other Mining Occupations	0.22
Production helpers	0.20
Janitors	0.20
Drillers of oil wells	0.19
Clothing pressing machine operators	0.18
Miners	0.16
Furniture/wood finishers, other precision wood workers	0.15
Fishers, marine life cultivators, hunters, and kindred	0.15

Table A3
Area analysis by subgroup.

VARIABLES	(1) OLS Δ log $\tilde{w}_{jkt}$	(2) IV Δ log $\tilde{w}_{jkt}$
All Workers	0.170***	0.027
	(0.033)	(0.075)
White	0.180***	0.069
	(0.035)	(0.073)
Minority	0.038	-0.618***
	(0.066)	(0.169)
Existing Immigrant	0.055	-0.592***
	(0.071)	(0.177)
HS Diploma or Less	-0.132***	-0.541***
	(0.046)	(0.115)
Some College or More	0.375***	0.347***
	(0.044)	(0.084)
Work Experience 1-5 years	-0.342***	-0.820***
	(0.111)	(0.225)
Work Experience 6-10 years	-0.084	-0.425**
	(0.090)	(0.191)
Work Experience 11-15 years	0.208**	0.066
	(0.088)	(0.176)
Work Experience 16-20 years	0.457***	0.491***
	(0.083)	(0.148)
Work Experience 21-25 years	0.433***	0.496***
	(0.081)	(0.173)
Work Experience 26-30 years	0.353***	0.505***
	(0.084)	(0.136)
Work Experience 31-35 years	0.146**	0.086
	(0.068)	(0.120)
Work Experience 36-40 years	0.189**	-0.132***
	(0.089)	(0.046)

1. Each cell presents the results from a unique regression for different subpopulations. Estimates are a variant of estimating Eq. (3). In all cases, we follow the existing literature and stratify labor markets by MSA, occupation (quartile), *and* potential experience. In the main text, we only stratify by MSA and occupation. Columns differ by estimation technique: column (1) uses OLS, while column (2) uses 2SLS and the shift-share instrument described in the paper. All regressions are weighted by the sample size used to create the average log weekly wage in a given skill group at time t. Robust standard errors are reported in parentheses. *p<0.01***, p<.05**, p<.10**.

Table A4
Reduced form estimates of s_{ijt}.

VARIABLES	(1) Educ-Exp (Borjas, 2003) w_{ijt}	(2) Educ-Exp (Our Replication) w_{ijt}	(3) Occ-Exp (Quartile) w_{ijt}	(4) Occ-Exp (Quintile) w_{ijt}	(5) Occ-Exp (Sextile) w_{ijt}	(6) Occ-Exp (Dorn) w_{ijt}
Weighted (All)	-0.572***	-0.568***	-1.177***	-1.190***	-0.983***	-0.663***
	(0.162)	(0.162)	(0.200)	(0.243)	(0.190)	(0.244)
	[-0.400]	[-0.398]	[-0.824]	[-0.833]	[-0.688]	[-0.464]
Ed/Occ Groups	4	4	4	5	6	4
Observations	192	192	192	240	288	192

1. Each cell represents a unique specification. Each column differs based on the definition of skill (education or one of the occupation groups with eight experience groups). The dependent variable is the mean of the log weekly wage of natives in each skill group. The independent variable of interest is the share of total employment by immigrants in a given skill group. All specifications include year fixed effects, occupation (or education in column 1) fixed effects, experience group fixed effects, and interactions of all fixed effects. Robust standard errors are reported in parentheses and the estimated elasticity is reported in square brackets. *p<.01***, p<.05**, p<.1**.
2. All regressions are weighted by the total number of natives used to calculate the average wage in each skill group.

Table A5
Changing Borjas replication.

VARIABLES	(1) Educ-Exp (My Replication) w_{ijt}	(2) Occ-Exp (Quartile) w_{ijt}	(3) Occ-Exp (Quintile) w_{ijt}	(4) Occ-Exp (Sextile) w_{ijt}	(5) Occ-Exp (Dorn) w_{ijt}
Weighted (Natives)	-0.481***	-1.217***	-1.26***	-1.054***	-0.717***
	(0.104)	(0.209)	(0.249)	(0.189)	(0.245)
Weighted (All; 2000 Census))	-0.367***	-0.884***	-0.649**	-0.721***	-0.496***
	(0.129)	(0.241)	(0.275)	(0.223)	(0.183)
Weighted (Natives; 2000 Census))	-0.389***	-0.893***	-0.656**	-0.729***	0.504***
	(0.131)	(0.240)	(0.275)	(0.224)	(0.186)
Education or Occupation Groups	4	4	5	6	4
Observations	192	192	240	288	192

Data Appendix

A. Sample description

Wage sample

We calculate mean log wages for male workers in each year. Following Borjas (2003), we restrict the sample to include non-self-employed males, aged 18-64, who have positive weeks worked, valid earnings data, and that did not live in group quarters. Mean log wages are represented as constant 2000-dollars and we used hours worked (perwt*weeks*hours/2000) as weights in the calculation. As in Borjas (2003), we use potential experience as a proxy for actual experience. To calculate potential experience, we assume that workers with less than a high school diploma enter the labor force at 17; workers with a high school diploma or GED enter the labor force at 19; workers with some college (less than a bachelor's degree) enter the labor force at age 21; and workers with a college degree enter the labor force at 23. We drop those who report potential experience less than 0 or greater than 40.

Employment sample

To calculate labor supply in each occupation-experience group, we limit the sample to males aged 18-64 who have positive weeks worked that did not reside in group quarters. Here, self-employed workers are included in the calculations. Labor supply in an occupation-experience group is the sum of all hours worked. Potential experience is defined as above.

B. Borjas (2003) Replication

One concern is that the results of our paper are driven by different sample selection criteria, variable construction, and/or weighting methods. To provide support for the analysis above, we present a replication of the work by Borjas (2003).

We start by noting the differences in our data and methodology from that of Borjas (2003). Borjas (2003) utilizes US Census data from 1960, 1970, 1980, and 1990; pooled CPS data from 1999, 2000, and 2001 to form 2000 data. The 1980 and 1990 data use the 5% extract for immigrant counts and 1% extract for native counts and native wage calculations. Regressions are weighted by the total sample size of the educ-exp-year cell (immigrants and natives). Immigrant share is defined in terms of the number of workers (not the share of hours worked by immigrants).

For the analysis in our paper, we make several changes to this original Borjas (2003) methodology and, instead, follow the sample selection from Borjas, Grogger, and Hanson (2012) (BGH, hereafter). For our analysis, we use US Census data from 1960–2010 with no differentiation between 1% and 5% extracts in 1980 or 1990. Though we use 2010 data in the main results of the paper, we omit 2010 in the analysis that follows. Regressions are weighted by the number of natives in each cell used to calculate the average wages. Immigrant share is defined as the percent of total hours worked.

Table A4 presents our replication of Borjas (2003). Each column represents a unique specification and all models include the full set of fixed effects described in the paper. Column (1) are the results reported by Borjas (2003). Column (2) presents our replication results. Columns (3)–(6) present the estimated impact of immigration on native wages using our occupation classifications when using these replication data. For comparison, the results in columns (2)–(6) should be compared to the estimates in Panel A of Table 2 and Panels C and D of Table 3 in the text.

Comparing columns (1) and (2) suggest a successful replication of Borjas (2003). Although not exact, the differences are trivial. There are, however, notable differences between the replication results and those in Section 3. When using the methodology of BGH and including the 2010 data, we estimate an elasticity of -0.119 that is not statistically significant. We address this point below. Furthermore, columns (3)–(6) suggest that data and methodology are not driving the results in the paper. In fact, when using the methodology in Borjas (2003), the estimated impacts are even larger than reported in Section 3.

Next, Table A5 reports estimates when we alter one of the components of the original Borjas (2003) replication. Again, each column represents a different specification using a different skill classification (as above). Row 1 reports estimates when we use the exact Borjas (2003) data but weight the regressions by the number of natives used to calculate average wages (as in BGH). Row 2 reports the estimates when we use the 2000 Census data (IPUMS) in place of the pooled cross-section from the CPS but utilize the weights in Borjas (2003). Row 3 reports estimates when we use the BGH weights *and* the 2000 Census data.

For each row, the reported estimates are smaller (in absolute value) when compared to Table A4. From row (1), however, the choice of weights has a relatively minor effect on the estimates. A more sizeable impact is seen in row (2). When we use the 2000 Census data in place of the CPS data, the estimates are much more in line with what we estimate in our paper. The differences (between row 2 of Table A4 and Table A5) are fairly large; however, there is only a statistical difference (at the 5% level) in the Quintile occupation group (although it is very close for most of the others).

Taken together, Tables A4 and A5 suggest that variable construction, sample selection, and the choice of weight are not driving the results in the paper. While notable differences exist in some specifications, the results presented in the paper are smaller (in absolute value). Thus, any data or methodological issues are working against the narrative of the paper.

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