Immigration and Native Wages: A New Look

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Abstract

Prior studies have examined the impact of immigration on native born wages. These studies have relied upon education-experience groups to define labor markets and identify the wage elasticity of supply of immigrants. However, evidence suggests that education is either of different quality or at least treated differently for immigrants leading to potentially biased conclusions. We utilize O*NET occupational characteristics to form a different set of labor markets. Our analysis finds higher impact on native born wages than prior work, as expected. While prior work finds that a 10% increase in immigrant workers results in a 2% decrease in earnings, our results suggest that a decrease of 4.5% to 6% is more likely.

JEL Classification: J24; J31; J61

Keywords: Immigration; Occupation-specific Skills; Native-Immigrant Complementarities

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1. Introduction

A simple labor market model of supply and demand implies that immigrant (or any migrant) entrance to a local labor market will result in falling wage, *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 through the popular press. However, as recent surveys suggest (Borjas, 1994; Kerr and Kerr, 2011) the results are far from uniform. A number of issues make estimation of the elasticity of earnings to immigration challenging. First, immigrant location decisions are endogenous, such that characteristics of local labor markets may be driving immigrant location decisions. This endogeneity may take several forms. Immigrants may choose to locate in high wage cities, natives may respond to immigrant inflows by moving, 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 move away from analyzing local labor markets; rather, researchers should use national-level data and treat the entire US as one labor market. A second, and important issues is constructing labor market cohorts. It has become standard in the literature to analyze the impact of immigration on similarly skilled natives within cohorts defined by education and work experience. This approach, pioneered in the immigration literature by Borjas (2003), implicitly assumes that within these cohorts, immigrants and natives are perfect substitutes. Recently, 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 cohorts (Card, 2009; Ottaviano and Peri, 2012; Manacorda et. al, 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.

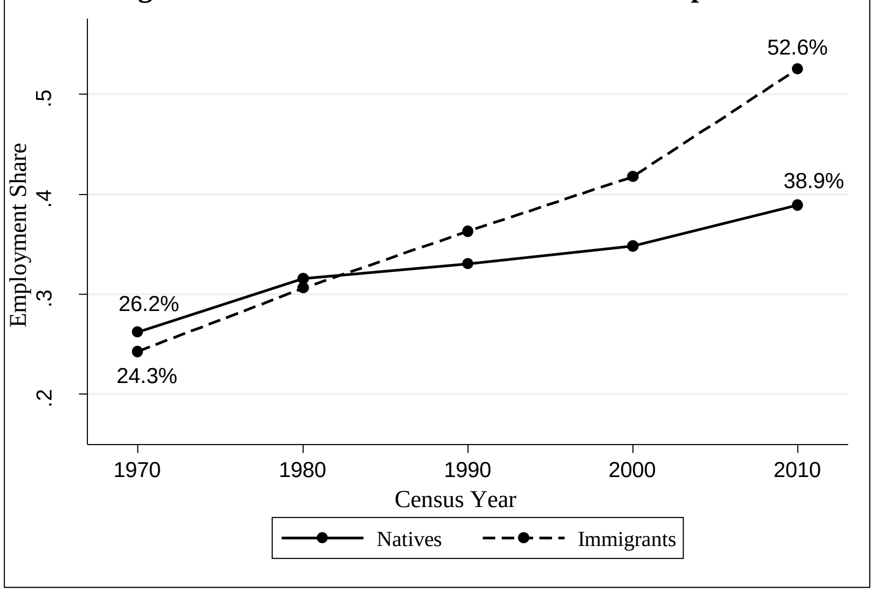
We claim that the incidence of imperfect substitutability arises due to the empirical model employed in previous studies – education is an imperfect proxy for overall skill level. To see this, consider three empirical regularities. First, there is a small literature examining the differential impacts of immigration on natives by race. In this literature, researchers stratify labor markets by education and race and find that immigration has a differential impact on black wages relative to white wages, but the evidence is mixed. Using the national labor market approach, Borjas et al. (2010) find that the impact of immigration is 33% lower on black men relative to white men. Altonji and Card (1991), who examine the impact of immigration on the wages of less-skilled (educated) workers using the area approach, find the opposite. Their first-differenced results (row 4 of Tables 7.8 and 7.9) suggest that a 10% immigration shock has a (roughly) 70% larger (more negative) effect on the average wage of less-skilled blacks than less-skilled whites. Though the results differ in the direction of the differential impact (which is likely due to differences in methodology and/or sample selection), it is clear that the impact of immigration is not constant across races within education groups. If education is a good proxy for overall skill, then one would expect the impact of immigration to be constant across all workers within an education group. The differential effects on black wages estimated in this literature, however, suggest whites and blacks are not perfect substitutes within education groups; thus, calling into question the use of education to stratify labor markets.

Second, there is significant wage dispersion *within* education groups (Levy and Murnane, 1992; Murnane, Willett, and Levy, 1995; Ingram and Neumann, 2006). This suggests that skills other than educational attainment are being rewarded in the labor market. If these skills are distributed differentially between immigrants and native born, but are also correlated with education, the approach can lead to bias. Third, immigrants earn less than similarly educated natives (Bratsberg and Terrell, 2002; Bratsberg and Ragan, 2002; Ferrer and Riddell, 2008; Friedberg, 2000). This fact has been attributed to differing employment distributions across occupations and a lower return to education for immigrant workers. The lower return to education itself suggests that educational attainment categories may be a poor measure of similar skills between immigrants and native born. A related argument is found in the geography literature when discussing the disparate value of "credentialized cultural capital" in determining immigrant/native wage gaps in Canada (Bourdieu, 1977; Reza, 2006). In this literature, credentialized cultural capital refers to the level of educational attainment. Although immigrants may have more credentialized cultural capital (higher educational attainment), domestic employers do not value education earned abroad as highly as education earned domestically.

Several feasible scenarios exist for the above differentials in returns to education. First, US employers may be simply discriminating against immigrants and either underpaying for their skills or refusing to hire immigrant workers (Borjas, 1990). While feasible, Bucci and Tenorio (1997) decompose the wage gaps between white natives and immigrants and find that the majority of the wage differential is simply US employers overvaluing native skills, not undervaluing immigrant skills. Similarly, Reimers (1983) documents that while discrimination may play a minor role in the wage gaps of Hispanic immigrants; differences in observable characteristics (i.e. language proficiency) explain the majority of the wage differences. Second, immigrants face differential returns to education because they are being "misplaced" in the labor market. That is, immigrants enter the US and are pushed toward jobs in which they possess too much education than the average worker. One reason for under-placement is that educational attainment is a subjective measure between countries and over time within countries. Peracchi (2006) notes that years of schooling or the schooling level may reflect varying levels of literacy in different countries. As researchers are interested in the effects of immigration on demographically comparable natives and many immigrants receive the entirety of their education abroad, stratifying labor markets by education may not identify immigrants and natives that directly compete in the labor market.

Because of differences in education standards across countries, immigrants may be misplaced because skills learned in the host country are not transferrable to the US labor market. While many cases of skilled immigrants taking unskilled jobs are reported in the national media, this fact is supported by the data (Mattoo et al., 2008; Neagu, 2009). Figure 1 confirms this phenomenon for low-skill occupations. The figure plots the percentage of native and immigrant workers with a high school degree or some college that work in low-skill occupations. Holding educational attainment constant, immigrants are more concentrated in less-skilled occupations and the gap is widening over time. Thus, it seems reasonable to assume that these workers will not directly compete in the labor market.

Figure 1: Share of Workers in Low-Skill Occupations



Further evidence of this phenomenon can be seen in Table 1 below. Table 1 presents the percent of workers that are classified as over-educated for their current job. Here, we define over-educated as having significantly more education relative to others working in the same occupation (more detail below). Table 1 uses occupation-specific education requirements from the O*NET and matches these data to US Census micro-data from 1970-2010. Specifically, we use O*NET data for the required level of education needed to adequately perform the job. These data give a value of 1-100 for 12 education groups, which map directly to the percentage of the total employment in each occupation that holds said level of education. We collapse these 12 education groups into 7 categories: less than high school, high school graduate (or equivalent), some college – no degree, Associate’s Degree, Bachelor’s Degree, Master’s Degree, and Doctorate/Professional Degree. We are interested in the share of the population who possess above average education for their current job. That is, they work in an occupation for which they hold significantly more education than the rest of the labor force in the given occupation. Using the data on required education, we group occupations based on the level at which the worker would be considered over-educated: over-educated if holding at least a bachelor's degree, over-educated if holding at least a master's degree, over-educated if holding a doctorate/professional degree, or never over-educated. We do not consider the case in which someone is over-educated for a job if they hold an associate's degree or some college but no degree. This follows from the wage structure literature which suggests that high school dropouts and high school graduates are perfect substitutes (Katz and Murphy, 1992).[3] The table presents over-education rates for natives, all immigrants, and immigrants who have been in the US for less than 5 years.

Table 1: Over-Education of Natives and Immigrants, 1970-2010

Occupation Group	**(1) % Over-Educated Natives**	**(2) % Over-Educated Immigrants**	**(3) % Over-Educated Immigrants (in US for less than or equal to 5 years)**
All Occupations	5.36% (6.33%)	9.25% (10.89%)	9.59% (11.06%)
Occupations where one is over-educated when holding at least a Bachelor's Degree	5.17% (6.67%)	7.55% (9.37%)	7.91% (10.02%)
Occupations where one is over-educated when holding at least a Master's Degree	6.70% (7.04%)	15.86% (17.81%)	18.95% (22.86%)
Occupations where one is over-educated when holding at least a Doctoral/Professional Degree	4.28% (4.43%)	12.74% (13.43%)	13.98% (14.75%)
Occupations where one is over-educated when holding at least a Masters or a Doctoral/Professional Degree	6.18% (6.48%)	15.18% (16.81%)	17.78% (20.74%)

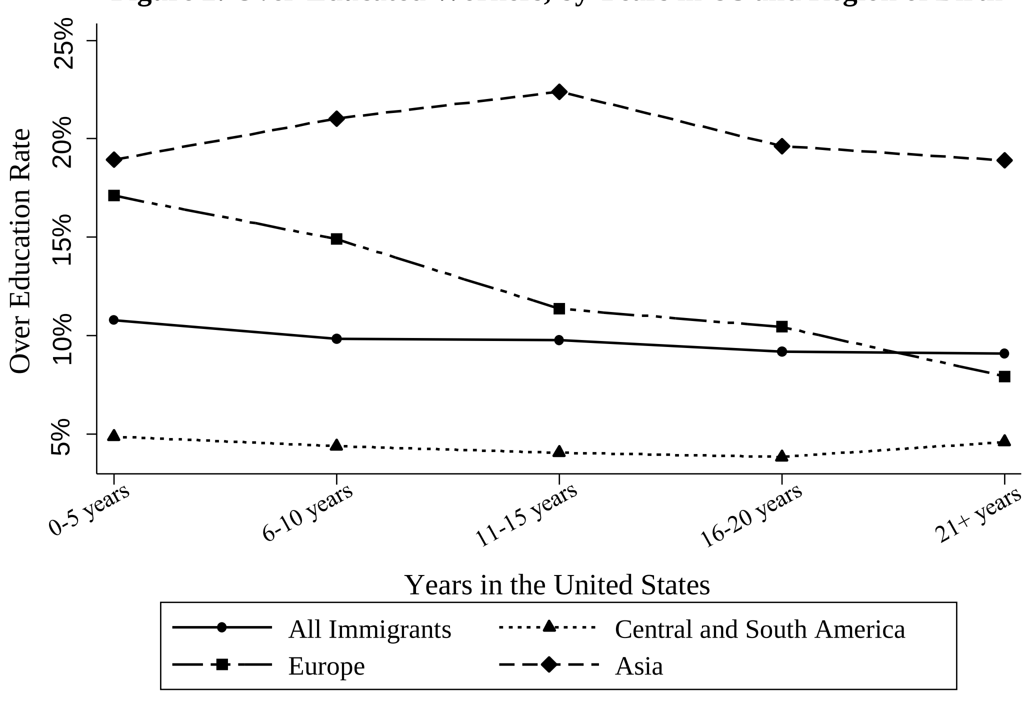
1) Hours weighted averages reported in parentheses.

The differences in over-education rates by nativity are significant, especially for those persons holding advanced degrees. For all occupations, immigrants are nearly twice as likely to be over-educated for their job compared to natives. In occupations that generally require a bachelor's degree, 15.2% of the

[3]Similarly, when grouping workers into high- and low-education groups, the authors allocate a share of the "some college, no degree" group to the low-education group. Thus, we follow this reasoning and assume that workers with less than a bachelor degree are not over-educated if they work in lower-skill jobs that typically do not require any college education.

immigrant workers hold an advanced degree compared to 6.2% of natives. Column (3) displays over-education rates for newly arriving immigrants. Unsurprisingly, new immigrants have higher over-education rates than the entire immigrant population, which may reflect the lack of transferability in immigrant skills upon entry (i.e. language skills). From the immigrant assimilation literature however, one would expect this rate to decline significantly as immigrants remain in the US. Figure 2 plots the over-education rates for immigrants across all occupations by length of time in the US and region of birth. Contrary to the assimilation hypothesis, the over-education rate for the entire immigrant population (solid line) is relatively constant over tenure in the US, around 10%. Because assimilation is affected by English proficiency and cultural similarities, we also present over-education rates by region of birth. The constant over-education rate persists for immigrants from Central and South America (dotted line) and Asia (dashed line). Though the magnitudes are different, the underlying trend is the same. For European immigrants (dash-dot line) however, over-education rates decrease over time, consistent with positive occupational mobility associated with assimilation. While decreasing, the over-education rate for the longest tenured immigrants is still roughly 9%.

Figure 2: Over-Educated Workers, by Years in US and Region of Birth



If it is the case that immigrants' educational attainment is treated differently in the labor market on, then previous studies analyzing wage impacts within education-experience cells may not tell the whole story. That is, immigrants and natives with the same education-experience profile may not be directly competing in the labor market, which would explain the negligible impacts found in the existing literature. While the under-placement scenario is the main focus, the discrimination scenario is not without merit. As Reimers (1983) indicated, discrimination plays a minor role in the immigrant-native wage gap. Thus, if this discrimination is in the form of employers preferring to hire native workers, this may force more immigrants into occupations for which they are over-educated.

For these reasons, we argue a better measure of labor market competition is to stratify the labor market by occupation. Existing studies incorporating occupations as a proxy for skill are relatively sparse. To our knowledge, only three such studies exist. 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 sizes, make 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 3 broad occupation categories. The authors estimate that the change in immigrants over the data period decreased wages in low-skilled, manual occupations 0.8% and had no impact for medium-skilled and high-skilled occupations.

The present study improves upon past research in several ways. First, following Borjas and Katz (1997) and Borjas (2003), we move away from the area studies of Card (2001) and Orrenius and Zavodny (2007) and treat the U.S. as one national labor market. Area studies have been criticized because they implicitly assume that native labor and capital do not adjust across labor markets in response to immigration. If the existing population relocates inputs to areas (or occupations) less affected by immigration, then the impact of immigration will be underestimated. Second, we construct occupation groups defined using skill data from the O*NET. Previous studies using occupations have relied on broad Census-defined occupation groups. The advantage of using the O*NET data is that we are able 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.

The rest of the paper is structured as follows. Section 2 outlines the data and the methodology used to define occupation groups. Section 3 outlines the potential problems with stratifying labor markets by education when analyzing the impact of immigration on native wages. We first analyze differences in employment shares of immigrants and natives along skill distributions. The results suggest that immigrants are underrepresented (overrepresented) in communicative (manual/physical) task intensive occupations. This result holds for the entire population and *within* education groups. Next, we analyze the differences in the rate of return to education paid to natives and immigrants. We show that immigrants are paid a lower rate of return than natives and this leads to a heavier concentration of immigrants in low-wage jobs. As discrimination has been shown to play only a minor role in immigrant-native wage gaps, this suggests that similarly educated immigrants and natives work in different jobs. Section 4 presents the empirical methodology and results similar to those in Borjas (2003). The results confirm the intuition above. When we stratify labor markets by occupations, the impact of immigration is nearly twice as large as those found in the existing literature. This result is robust to several different definitions of occupation groups and when we control for selection problems associated with occupations. In section 5, we address the concern that the use of occupation-defined skill groups may introduce bias. Using the traditional education-experience skill cohorts, we show that the impact of immigration on the wages of demographically comparable natives within *education* groups is quantitatively similar to the estimated impact when using cohorts defined by occupational skill. As such, the impact on wages is muted because immigrants and natives are imperfectly substitutable within education groups. Section 6 concludes.

2. Data

We draw from several data sources in this paper. Labor supply and wage data are 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 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.

We sort workers into skill groups based on potential experience and occupation. 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.).

2.1 Occupation Groups

The occupation groups constructed in this paper follow from a recent paper by Peri and Sparber (2009). 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.

Occupation-specific task indices are constructed using the Department of Labor's O*NET survey, which provides comprehensive data on characteristics of occupations. The O*NET content model is partitioned into several different domains, each providing different worker-specific and occupation-specific data. Unlike Peri and Sparber (2009), we make use of *both* worker-specific data on abilities, knowledge, and skills *and* occupation-specific data on work activities to generate these task intensity indices (throughout the rest of the paper, we will refer to all four of these measures as "skill groups").[4] Table A1 of the Appendix lists each skill used in constructing the task intensity indices.

One challenge when working with occupations over this many Census years is that occupation classifications change over time. Additionally, O*NET data are assigned to 2000 SOC (standard occupation classification) occupations. To remedy this problem, we use a modified occupation classification developed by Autor and Dorn (2013) (AD classification, hereafter). This occupation classification system creates a consistent, balanced panel of occupations across all years. To construct the occupation groups used in this paper, we merge skill data from the O*NET survey to the AD classification and group occupations on the basis of their occupation-specific skills.

The O*NET data assigns each skill 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.[5] To create the occupation-specific skill index, we first standardize the importance and level scores such that each has a range of 0-100. Then, we create a normalized "task-intensity score" (TS) for each skill by multiplying the standardized importance score and standardized level score – a higher task-intensity score suggests a given task is more important to performing a given occupation. We then calculate the average manual and communicative task-intensity score for each skill group and occupation. For example, within the worker ability domain, both physical abilities and psychomotor abilities are classified as manual abilities. Thus, for each occupation, we calculate the average manual task-intensity score by averaging the task-intensity of physical and

[4] Peri and Sparber (2009) rely solely on "abilities" from the O*NET survey.

[5] Importance and Level scores measure different aspects. There are occupations in which a given skill is equally important; however, one occupation needs to use the skill at a much higher level. An example from the O*NET is speaking ability for lawyers and paralegals. Speaking is important in both occupations; however, lawyers need a high level of speaking skills to argue cases, while paralegals simply need an average level of speaking skill (https://www.onetonline.org/help/online/scales).

psychomotor abilities. Lastly, the final manual (communicative) task-intensity score is the average of all skill group specific manual (communicative) task-intensity scores. Analytically, the manual task intensity index for each occupation (j) is calculated as[6]:

$$(1) \qquad M_j = \frac{1}{n}\sum_i \left(\overline{TS}_{ij}\right) \quad \forall \; i = (Ability, Knowledge, Skill, Work\ Activity).$$

For each occupation in the AD classification, we create the ratio of communicative task intensity to manual task intensity, which is the basis for defining our occupation groups. From this ratio, we construct three occupation classifications based on the distribution of this skill ratio across occupations: 1) a four occupation group classification where each group is a quartile of the distribution, 2) a five occupation group classification where each group is a quintile of the distribution, and 3) a six occupation group classification where each group is a sextile of the distribution.

As the above classifications are rather crude treatments of the data, we construct a fourth occupation classification that allows the data to determine the optimal cutoffs. One concern with the above classifications is the definition of manual skills. There are obvious occupations that require significant manual tasks relative to communicative tasks (i.e. construction laborers, miners, etc.); however, there are other occupations (i.e. dancers and performers) that have similar values of manual task intensity that are clearly not competing with construction laborers for jobs. While we attempt to control for this by using both the importance score and level score above, another feasible way to alleviate this problem is to first classify occupations into blue-collar and white-collar occupations. Then, we use cluster analysis to determine the optimal number of occupation groups.[7]

3. Occupation Groups vs. Education Groups

The concern of the present research is that by stratifying labor markets by education, researchers do not compare immigrants and natives that will directly compete in the labor market because 1) immigrants are under placed in the labor market and 2) immigrants and natives work in different occupations. Below, we present two empirical exercises that illustrate this point.

3.1 Misplacement of Immigrants in the Labor Market

To illustrate the first point, we provide an empirical analysis in the spirit of Dustmann et al. (2012). Specifically, we compare across the native wage distribution the actual immigrant earnings

[6] Construction of the communicative task intensity index is constructed analogously.
[7] It is determined that a five group occupation classification is optimal (based on maximizing the Bayesian Information Criterion (BIC)): two clusters in the blue-collar sector and three clusters in the white-collar sector. We also use several other methods and in almost all cases, the methods agree on the optimal number of clusters. These results are available upon request.

distribution to a counterfactual immigrant earnings distribution. The counterfactual distribution is the share of immigrants along the native wage distribution if immigrants were paid the same rates of return to observable characteristics as natives.

We construct the employment distributions using micro-data from the 2000 U.S. Census (IPUMS). Sample criteria are discussed in the Data Appendix. First, we estimate the rates of return to observable characteristics for *native* workers via a typical log wage model[8]:

$$w_i = X_i\beta + \theta_k + \varepsilon_i; \tag{2}$$

where w_i is the log hourly wage for individual i; X_i is a vector of demographic variables including categorical variables for education and experience, an interaction of education and experience, race, and marital status; and θ_k is a vector of state fixed effects controlling for wage differentials across states. Next, the estimated coefficients are used to predict the wage for each *immigrant* in the sample. In other words, we predict the wage an immigrant would have earned had they received the same rates of return as a native worker. Once we have obtained the predicted wage, each immigrant in the sample is ranked according to their actual and predicted wage in the native wage distribution in year *t.*

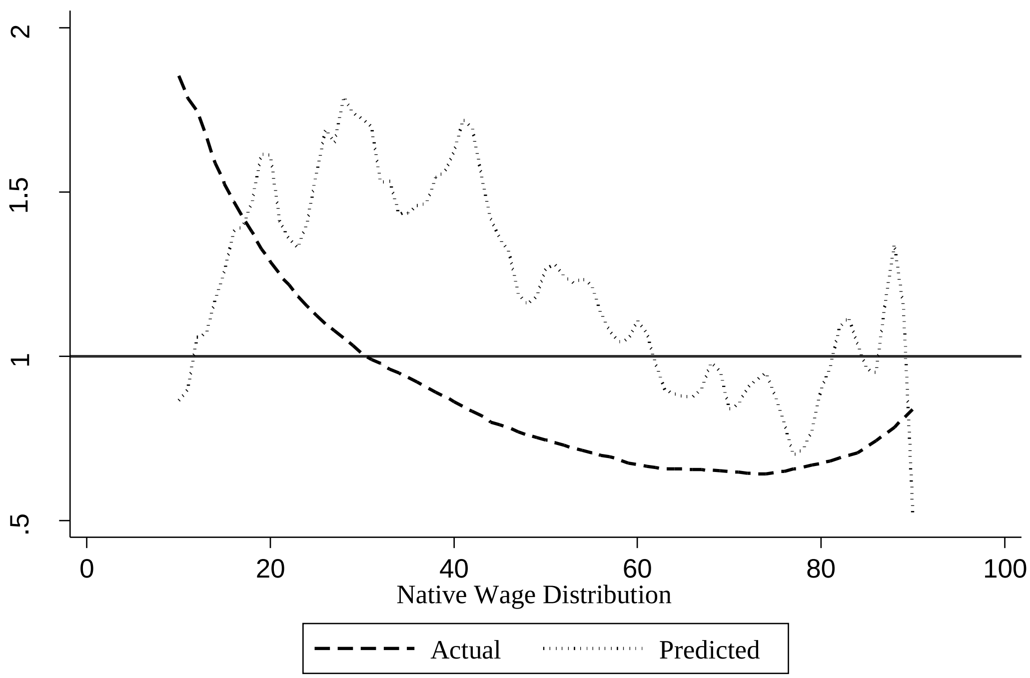
Figure 3 below plots the kernel estimates of the *relative* density of the log odds ratio along the native wage distribution.[9] As we plot relative densities, the horizontal line at one represents the actual native density; thus, if the immigrant density is above one, immigrants are overrepresented in this portion of the native wage distribution (and vice versa). The dashed line represents the observed relative density for immigrant wages. The plot of observed wages suggests that immigrants are overrepresented below the 35th percentile of the native wage distribution. The dotted line represents the plot of the counterfactual relative density. The plot illustrates the potential problems with defining skill cohorts based on demographics. The differences in the actual density and the predicted density are significant and confirm the discussion on misplacement of immigrants in the labor market with regards to educational attainment. First, based on observable demographics, too many immigrants reside in the lower tail of the native wage distribution. Second, while we actually observe immigrants in the bottom 35% of the native wage

[8] The model is estimated on male workers only. The regression is weighted by the person weight from the Census and robust standard errors are clustered by education and potential experience. Also, hourly wage is "Winsorized" such that the lower bound of hourly wage is 75% of the federal minimum wage in year t and the upper bound is 50 times the minimum wage in year t (Card, 2009).

[9] Because the variable of interest, the position of immigrants along the native wage distribution, is bounded between 0 and 1, kernel estimates on the untransformed variable would give misleading estimates at the extreme (Dustmann et al., 2012). To mitigate this concern we 1) estimate the kernel on the log odds ratio and 2) report the kernel estimates for the 10th-90th percentiles only.

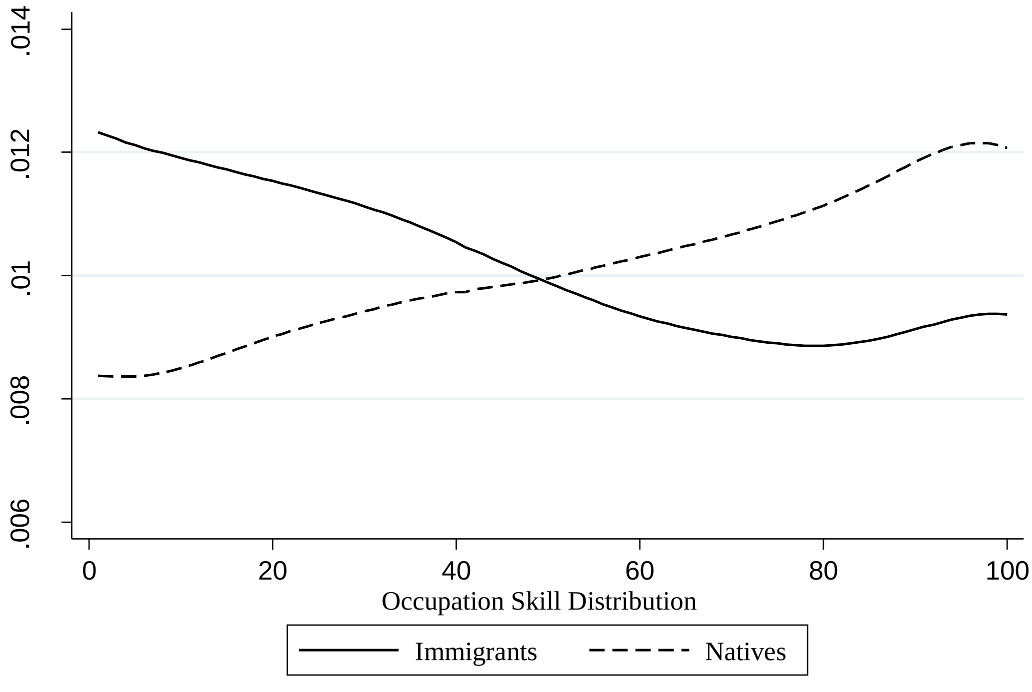
distribution, the counterfactual distribution suggests immigrants should be clustered from roughly the 20th to 60th percentiles.

Figure 3: Actual vs. Predicted Positions of Immigrants Along Wage Distribution



Two plausible scenarios exist for the differences in the distributions in Figure 3. First, either U.S. employers undervalue foreign education or overvalue domestic education. While Figure 3 does not allow differentiation between these two scenarios, either one would lead to under-placement of immigrants in the labor market. Second, omitted variables are driving the differences. Namely, we are unable to control for English speaking ability in (2). Because we estimate (2) on the *native* population, English proficiency cannot be included as it does not vary within the native sample. While omitted variables are a threat to the interpretation of the *differences* in the distributions above, they would not alter the interpretation that stratifying the labor market via educational attainment is problematic in the context of immigration. To see this, consider two workers. One is a U.S. native who recently graduated with a bachelor's degree while the other is an immigrant with a recent bachelor's degree but limited English proficiency. It is not hard to imagine a scenario in which these two workers accept drastically different occupations although they have similar education and work experience. This fact would explain their relative positions along the native wage distribution, but it would not change the fact they do not compete in the labor market despite equal educational attainment and work experience. As such, we take Figure 3 as support for our claim that education-specific skill groups are problematic in the context of immigration.

Figure 4: Employment Along Occupation-Specific Skill Distribution



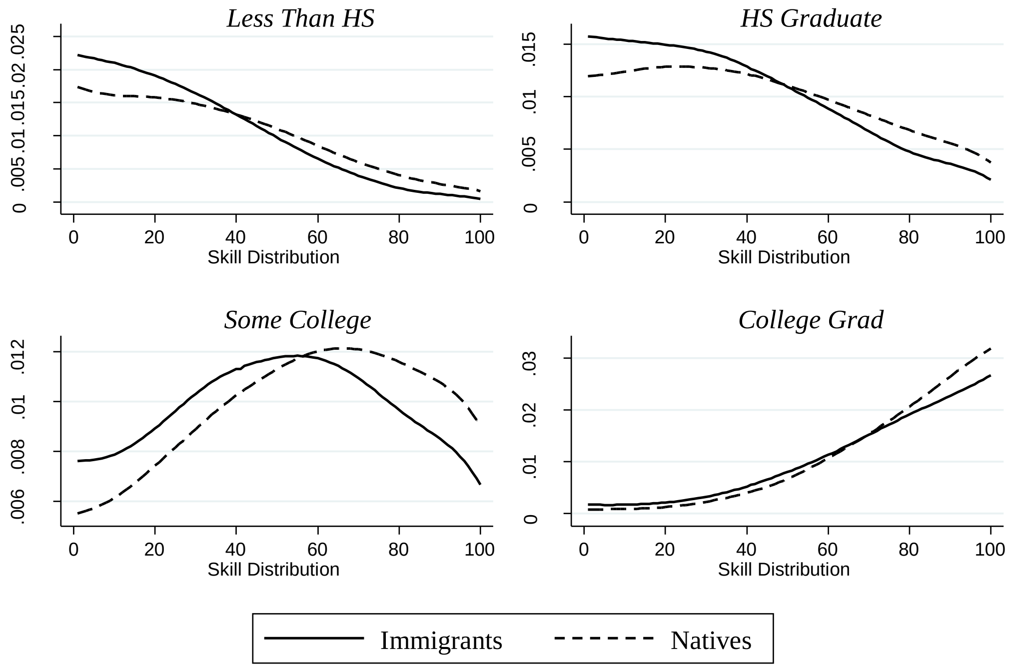
3.2 Differences in Immigrant and Native Employment Distributions

Peri and Sparber (2009) suggest that immigrants have comparative advantage in manual/physical tasks while natives have comparative advantage in communicative tasks. As such, immigrants and natives sort into and specialize in occupations intensive in the task for which they have comparative advantage. If this occupational sorting exists *within* education groups, it may explain the negligible impacts of immigration estimated in previous models.

To test this, we examine the employment distribution of immigrants and natives along the distribution of occupation-specific skills. Figure 4 plots the percentage of total hours worked by immigrants and natives from 1970-2010 along the distribution of the ratio of the communicative task intensity index to the manual task intensity. The differences in employment are striking and make clear that immigrants and natives are distributed differently across occupation-specific skills. Relative to natives, immigrants are overrepresented in jobs that require more manual tasks and underrepresented in those jobs that require more communicative tasks.

While informative, this fact is only important in the context of this analysis insomuch as these differences persist within education groups. Figure 5 shows the distribution of employment shares for each of the four education groups typically found in the immigration literature (less than high school, high school graduate or equivalent, some college, college graduate with at least a bachelor's degree). For all four education groups, the result is the same: immigrants are overrepresented in manual task intensive occupations relative to natives while underrepresented in communicative task intensive occupations.

Figure 5: Employment Along Skill Distribution, by Education Group

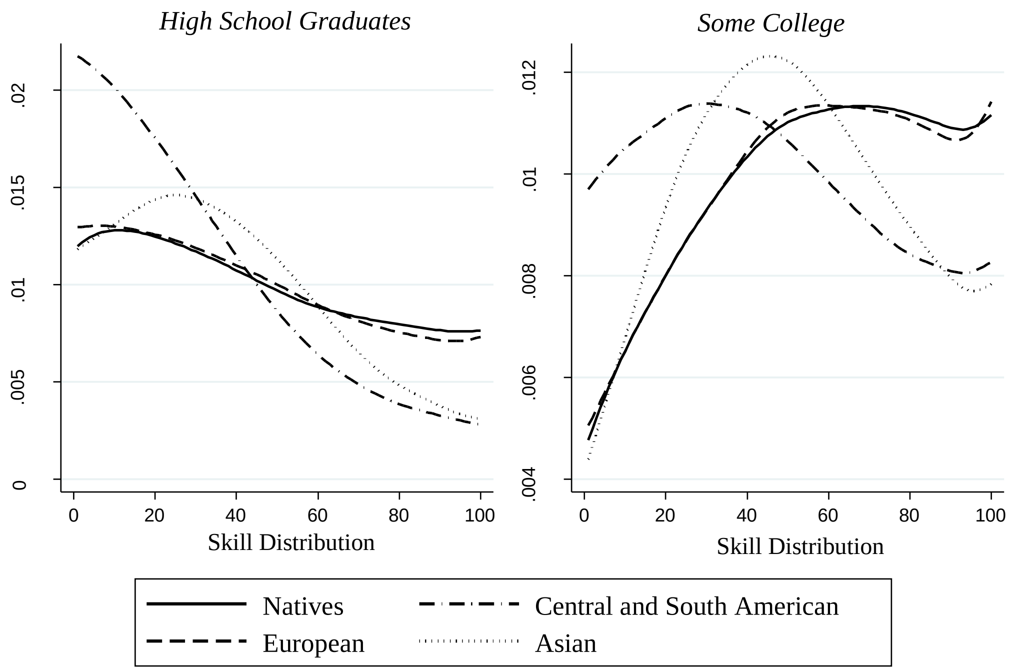


While the same general result holds within education groups, the differences between immigrant and native employment shares are modest. This result is unsurprising as the immigrant population is significantly more heterogeneous than the native population with respect to educational attainment and education quality. Countries differ in terms of school quality, curriculum, resources available to schools, and teacher standards (Peracchi, 2006). As such, one would expect the transferability of general education skills to differ based on an immigrant's country of origin. Figure 6, which plots employment shares along the skill distribution by region of birth, confirms this phenomenon.[10] Employment outcomes differ widely by region of birth and these differences are likely attributable to the English proficiency. European immigrants (dashed line) face similar labor market experiences as the native population (solid line); however, Asian and Central and South American immigrants face significantly different employment outcomes and are driving the differences in Figures 4 and 5. Asian immigrants (dotted line)

[10] For the sake of brevity, we only display the high school graduate and some college education groups. However, the general result holds for the other two groups as well. These figures are available upon request.

are clustered around the median of the distribution (e.g. occupations within the service industry), while Central and South American immigrants (dash-dot) are concentrated at the lower tail of the distribution (e.g. manual task intensive occupations).

Figure 6: Employment Along Skill Distribution, by Nativity



Ultimately, the results in this section complement the findings in the previous section. Education is a subjective measure of skill. Simply stratifying labor markets by education does not necessarily compare immigrants and natives who will directly compete in the labor market. Immigrants and natives cluster in occupations in which they have the comparative advantage. This holds within education groups and across the immigrant population. Stratifying labor markets by occupation will form labor market cohorts with a greater degree of homogeneity with respect to skill in which immigrants and natives are perfect substitutes.

4. Empirical Methodology and Results

4.1 Empirical Model

The empirical model is derived from a theoretical framework of the demand side of the labor market. Assuming output is produced using a CES production function where labor and capital are separable, the relative wage of a given skill group is a function of 1) the population share within the group and 2) a group specific productivity component.[11] Following Borjas (2003), this group-specific productivity component is absorbed by a collection of fixed effects:

$$w_{ijt} = \beta s_{ijt} + \theta_i + \varphi_j + \tau_t + (\theta_i * \tau_t) + (\varphi_j * \tau_t) + (\theta_i * \varphi_j) + \varepsilon_{ijt}. \qquad (3)$$

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 fact that the impact of occupation or experience on average wages may change over time. 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.

Equation (3) is estimated via OLS and the estimated coefficients are reported in Table 2. Each column/row of table 2 represents a different specification of (3). The columns differ by skill group classification (i.e. Education-Experience, Occupation (4 group)-Experience, etc.). Row 1 reports the weighted estimates, where the weights are the number of observations used to calculate the average wage within a cell. Row 2 reports the corresponding elasticities from the estimated coefficients in row 1.[12] Row 3 presents unweighted estimates, while row 4 reports estimates when we include native labor force as an explanatory variable. Because the key explanatory variable is simply the immigrant share of total hours worked within a skill group, an increase in s_{ijt} would occur from either an increase in immigrant labor supply *or* a decrease in native labor supply. As such, the estimates in row 4 report the impact of s_{ijt} holding native labor supply constant.

First, column (1) reports estimates of (3) using the traditional education-experience classification found in the existing literature.[13] The baseline results are slightly lower than those found by Borjas

[11] For derivation of the model in the context of immigration, I refer interested readers to Card (2001) or Borjas (2003).
[12] The share of immigrants within a skill group (s_{ijt}) in Eq. 3 is not in log form rather an approximation. As such, we calculated the corresponding elasticities as in Borjas (2003).
[13] In this specification, we use the four-group classification described above (Less than HS, HS grad, some college, college grad).

(2003).[14] Focusing on the estimated elasticity in row 2, the results suggest that a 10% supply shock (an inflow of immigrants that increases total hours worked within an education-experience cohort by 10%) will reduce native wages by a modest 1.9%. Columns (2) – (6) use different occupation classifications in the estimation of (3). Columns (2) – (4) use occupation groups defined by the distribution of the communicative-to-manual task intensity ratio. When we group workers based on occupation-specific skills, the estimated impact of immigration is much larger. Again, focusing on the elasticities in row 2, the results suggest a 10% supply shock within a given occupation-experience cohort will decrease native wages by 7.2%, 5.6%, and 6.1%, respectively. Column (5) uses the clustered classification that first separates workers by white-collar/blue-collar status then groups workers based on occupation-specific skill. In this specification, the estimated impact of immigration is similar to those above and suggests that a 10% increase in the number of immigrants within a cohort will decrease the average native wage by 5.4%.

Table 2: Reduced Form Estimates of s_{ijt}

	(1) Educ-Exp	(2) Occ-Exp (Quartile)	(3) Occ-Exp (Quintile)	(4) Occ-Exp (Sextile)	(5) Occ-Exp (Cluster)	(6) Occ-Exp (Dorn)
VARIABLES	w_{ijt}	w_{ijt}	w_{ijt}	w_{ijt}	w_{ijt}	w_{ijt}
Weighted	-0.259*	-0.978***	-0.760***	-0.826***	-0.736***	-0.254
	(0.134)	(0.147)	(0.267)	(0.193)	(0.255)	(0.174)
Elasticities	-0.190	-0.718	-0.558	-0.606	-0.540	-0.186
Unweighted	-0.354***	-0.908***	-0.811***	-0.839***	-0.689**	-0.454***
	(0.103)	(0.171)	(0.252)	(0.161)	(0.334)	(0.149)
Includes Native Labor Force	-0.213**	-0.909***	-0.685***	-0.864***	-0.724***	-0.293
	(0.099)	(0.130)	(0.247)	(0.165)	(0.209)	(0.243)

1) Each column and row represents a unique specification. Each column differs based on the definition of skill (education or one of the occupation groups), while each row differs based on the label – weighted regression of (3), the corresponding elasticities of the weighted regressions, unweighted regression of (3), and the weighted specification including the native labor force as a regressor. The dependent variable is mean of the log weekly wage of natives in each skill group. The independent variable of interest is the share of total hours worked 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 clustered by skill group are reported in parentheses.
2) Weighted estimates in row 1 and 4 are weighted by the total number of natives used to calculate the average wage in each cohort.

[14] 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 used the methodology above and the same data described in Borjas (2003) and produced a very similar result. Thus, the methodology used above is consistent with the past literature.

The results support the hypothesis that defining skill groups on the basis of education may attenuate the effects of immigration. By grouping workers into skill groups defined by occupation, the estimated impact on native wages is 2-3 times larger depending on specification. From rows 3 and 4, the results are not sensitive to using weights or controlling for native labor supply.

Concern arises that our results are not driven by a careful construction of markets, but rather by other factors associated with defining occupational groups. To test this, we estimate (3) using the occupation classification system developed by Autor and Dorn (2013). The results are reported in column (6). Recall that 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.[15] 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 columns (2)-(5). When using this occupational group classification however, the impact of immigration is significantly lower and similar in magnitude to the estimates when using education-based skill groups. This is unsurprising as AD rely on average educational attainment when constructing these groups, not occupation-specific skills.[16] To see this in the data, Figure 7 plots the share of total hours worked along the distribution of our skill ratio within AD occupation groups. Panels A and B are white-collar jobs (i.e. management occupations, etc.) and panels C and D are low-wage blue-collar jobs (i.e. construction). Though labor supply is skewed in the expected direction for each occupation group (white-collar occupations are skewed to the right hand side of the distribution, 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. Thus, we take the result in column (6) as support for the claim that occupation-specific *skills*, not occupations themselves, are the important component in constructing skill groups for which labor market competition is identified.

4.2 Robustness Checks

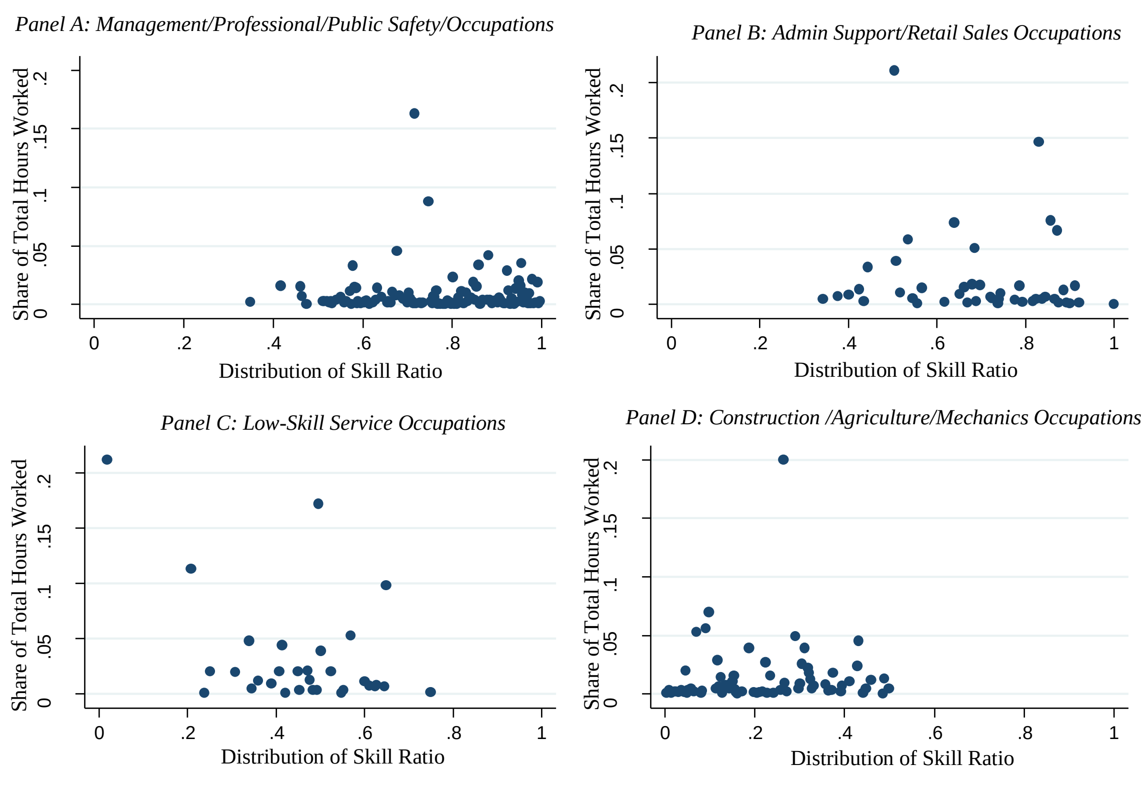
While the estimates in column (6) of Table 2 suggest that occupation-specific skills are what are important when defining skill groups, at least two concerns arise when stratifying labor markets by occupation. First, we only observe those individuals who are presently working in a given occupation, not all workers who *could* work in these occupations given a change in local labor market conditions. Second, as occupational choice is conditional on labor market conditions, we would expect natives to switch occupations in response to an immigrant inflow. In both cases, these selection issues would cause

[15] 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.

[16] In describing one of the occupation groups, the authors claim: “Technical, sales, and administrative support occupations cover a workforce that is on average better educated than any other occupation group apart from managers and professionals”.

us to overstate the impact of immigration on wages. Following Card (2001), one can alleviate these two concerns by treating a worker's occupation as a probabilistic outcome that depends on observable characteristics. In other words, each worker has some probability (π_j), based on observable characteristics, of working in occupation group 1,..., J. Then, total labor supply in a given occupation group is simply the sum of these probabilities.

Figure 7: Employment Along Communicative-to-Manual Skill Ratio



To incorporate this idea into the above analysis, we first estimate the probability that an individual would work in a given occupation group using a flexible multinomial probit model for each year and for immigrants and natives separately. For both the native and immigrant specification, we control for potential experience, race, marital status, education, an indicator for living in a high-immigration state, and region fixed effects in all models. In the immigrant specification, we also control for country of birth and years in the U.S.[17] Next, we calculate the average log weekly wage of all workers who could work in a given occupation group, which is a weighted average using the predicted

[17] A full description of these models and methodology can be found in the Data Appendix.

probabilities ($\hat{\pi}_j$) as weights. We then re-estimate (3) using this measure of labor supply and wages and data from 1970-2010. The results are reported in Table 3.

Table 3: Robustness Check, Impact of Immigration (1970-2010)

	(1)	(2)	(3)	(4)
	Educ-Exp	Occ-Exp (Quartile)	Occ-Exp (Quintile)	Occ-Exp (Cluster)
VARIABLES	w_{ijt}	w_{ijt}	w_{ijt}	w_{ijt}
Immigrant Share (s_{ijt})	-0.307**	-0.741***	-0.681***	-0.623**
	(0.126)	(0.1105)	(0.1621)	(0.2661)
Elasticity	-0.225	-0.544	-0.500	-0.457
Observations	160	192	240	240
R-squared	0.997	0.999	0.998	0.999

1) Each column represents a unique specification. Each column differs based on the definition of skill (education or one of the occupation groups). The dependent variable is mean of the log weekly wage of natives that *could* work in a given skill group. The independent variable of interest is the share of total hours worked by immigrants that *could* work 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 clustered by skill group are reported in parentheses.
2) All specifications are weighted using the total number of natives used to calculate the average wage in each cohort as weights.

Again, the estimated coefficients from the weighted regression are reported in row 1 and the corresponding elasticities in row 2. Column (1) of Table 3 reports estimates using the education-experience classification as a benchmark[18]. The benchmark elasticity is around -0.224. The estimated wage effect is lower (less negative) in columns (2) – (4) relative to the estimates in Table 2, however the difference is small and the main conclusion, that education groups are not sufficient for this type of analysis appears to be supported. Thus, when we account for the selection issues of occupational choice, we still conclude that a 10% immigrant supply shock will reduce average native wages by around 5%.

5. 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 cohorts is to estimate the impact of immigration on the wages of demographically comparable natives. To this point, we have argued that occupation-experience cohorts are superior to education-experience cohorts because we define skill groups for which

[18] The slight differences in the point estimates in Tables 2 and 3 stem from the loss of 1960 data.

immigrants and natives directly compete in the labor market. That is, immigrants and natives with similar work experience are perfect substitutes within occupations while imperfect substitutes within education groups. While this has been shown to be true above, two additional concerns arise from the above methodology.[19] First, there may be some concern regarding the seeming arbitrariness with which we define the number occupation groups.[20] Second, occupational choice of immigrants is potentially endogenous. Immigrants may choose occupations based on favorable labor market conditions. If so, the estimates in Table 2 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 Table 2 would be biased downward.[21] It is this concern that influenced the use of education-experience cohorts in the early literature.

An alternate 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 cohort. The use of education-based skill cohorts in this section is advantageous 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 Table 2 result from defining more homogeneous skill groups or bias introduced by using occupations. Second, this analysis provides a test to our claim that imperfect substitutability within education groups is the primary force behind the counterintuitive 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 less the 1960 census[22], the following probit model on male workers for each year separately:

$$(4)\ \Pr(I_i = 1) = \Phi(\beta X_i + \gamma OCC_i + \delta GEOG_i)$$

where 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, disability status, and a quadratic in potential experience; OCC_i is a vector of occupation-specific controls including AD occupation group fixed effects

[19] Another potential concern is the use of occupation defined skill groups while treating the U.S. as a single labor market. This national labor market approach has been widely adopted in the literature when assessing the impact of immigration on native wages. However, previous studies using occupation groups have used the area approach – treating metropolitan areas as their own distinct labor market. We have estimated the *local* labor market effect of immigration treating individual metropolitan areas as local labor markets. The results are similar (an elasticity of -0.4) and available upon request.
[20] While this is a legitimate concern, we have estimated the above model using occupation classifications with as many as 10 occupation groups (dividing the skill distribution by centiles) and the underlying result does not change. These results are available upon request.
[21] We tested for endogeneity of occupational choice across skill groups. When regressing immigrant penetration in a particular skill group (s_{ijt}) on lagged native wages (w_{ijt-10}), the resulting coefficient is not statistically significant and essentially zero.
[22] The 1960 Census data does not have as rich of a set of demographics as the later Census'

and industry fixed effects; $GEOG_i$ is a vector of geographic location controls including metropolitan status, state fixed effects, and a state-by-metro interaction.[23] 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: Native Worker Characteristics by Intensity of Competition with Immigrants

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Observations (N)	**660,275**	**660,503**	**660,775**	**661,228**
Weekly Wage	$435.98	$479.31	$522.62	$491.26
Hours Worked per Week	40.59	40.95	41.15	40.93
Weeks Worked per Year	48.26	48.95	48.94	48.87
Part-Time Workers	21.08%	18.66%	17.87%	18.90%
Potential Experience	17.69	18.77	19.09	19.44
White	91.90%	87.54%	84.14%	62.11%
African-American	8.10%	12.43%	15.38%	16.54%
Live in Metropolitan Area	35.54%	77.17%	91.43%	95.11%
Education Groups				
Less Than High School	3.17%	4.32%	5.06%	8.25%
High School Graduate (or GED)	35.64%	39.31%	38.17%	43.85%
Some College	27.09%	26.74%	25.77%	27.33%
College Graduate	34.10%	29.63%	31.00%	20.57%
Occupation Groups (AD)				
Management & Professional	44.25%	43.22%	43.11%	37.63%
Administrative Support & Retail Sales	42.18%	36.70%	33.74%	30.56%
Low-Skill Services	8.27%	11.65%	12.83%	19.00%
Precision Production & Craft	1.27%	1.75%	2.15%	2.58%
Machine Operators & Assemblers	1.87%	3.87%	5.11%	6.36%
Transportation, Construction, Mining, Agricultural	2.16%	2.82%	3.07%	3.86%
Select Industry Groups				
Manufacturing	8.65%	11.74%	12.46%	13.66%
Business and Repair Services	2.61%	4.05%	4.94%	5.62%

[23] I also estimated a more flexible specification of this model including a quartic in potential experience and a full set of education-by-demographic interactions and the results are quantitatively similar. These results are available upon request.

Personal Services	0.95%	1.87%	2.70%	5.44%
Professional Services	42.38%	39.58%	37.84%	34.45%
Public Administration	9.63%	5.45%	5.38%	2.84%
Occupation-Specific Skill Ratio	6.14	6.05	6.07	5.50

Table 4 reports the average labor market and demographic characteristics of native workers in each of the 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). Hours worked, weeks worked, potential experience, and the percentage of workers who are part-time are all fairly constant across quartiles. Perhaps counterintuitively, average weekly wages are *higher* among natives that are *more* likely to compete with immigrants in the data. However, this confounding result can be explained by the fact that those in quartiles 3 and 4 are much more likely to reside in metropolitan areas where wages are higher. In addition, native minorities are much more likely to compete with immigrants—the proportion of white workers decreases uniformly across the quartiles. Lastly, the differences across education, occupation, and industry groups are as expected. Native workers who are more likely to compete with immigrants are those with less education and work in low-skill occupations that require less communicative skills.

To estimate the impact of immigration on the native wages, we estimate the same reduced-form model in equation (3). The lone difference is the dependent variable is now the average log weekly wage of demographically comparable immigrants within a given education-experience cohort. The results are presented in Table 5 below. As a baseline, column (1) reports the estimates from above using education-experience cohorts. Again, the estimated elasticity is around -2. Columns (2) – (5) report the estimated impact on the wages of 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, we see that the theory does not hold. The impact of immigration is increasing across intensity quartiles. The impact of immigration is strongest on the wages of quartile 4 – the native workers most likely to compete with immigrants in the labor market. The elasticity suggests that a 10% immigration shock would decrease the wages of these natives by 4.3%. Like the results in the previous section (tables 2 and 3), the estimated elasticity is higher than those typically found using only the simple education-experience cohorts. We conclude, it is not endogeneity of occupational choice that is driving the estimates in section 4; rather, it is the construction of a more homogeneous group of perfectly substitutable workers that directly compete in the labor market.[24]

Table 5: Impact on Demographically Comparable Natives

VARIABLES	(1) All Natives w_{ijt}	(2) Quartile 1 w_{ijt}^{Q1}	(3) Quartile 2 w_{ijt}^{Q2}	(4) Quartile 3 w_{ijt}^{Q3}	(5) Quartile 4 w_{ijt}^{Q4}
Immigrant Share (s_{ijt})	-0.307**	0.099	-0.349**	-0.385***	-0.587***
	(0.126)	(0.144)	(0.134)	(0.137)	(0.104)
Elasticity	*-0.225*	*0.072*	*-0.256*	*-0.282*	*-0.431*
Observations	160	160	160	160	160
R-squared	0.997	0.997	0.998	0.998	0.999

1) Each column represents a different specification. The dependent variable is the 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. The independent variable of interest is the share of total hours worked by immigrants in each education-experience group. Robust standard errors clustered by skill group are reported in parentheses.
2) All regressions are weighted. The weights are the sample size used to create the average log weekly wage in a given cohort.

6. Conclusion

"Who competes with whom?" is an important question when trying to understand the impact of immigration on native wages. The existing literature assessing the impact of immigration on native wages has yielded contradictory results. The majority of these studies find little evidence that immigration has adversely affected labor market outcomes of natives. In this paper, we attribute these counterintuitive results to the fact that previous attempts have failed to compare immigrants and (demographically comparable) natives who directly compete in the labor market. We show that education is an imperfect proxy for skill in the labor market. Because immigrants and natives specialize in different skills and immigrants are often under placed in the labor market, immigrants and natives tend to cluster in different occupations.

[24] We have also estimated the initial probit models without occupation and industry fixed effects and the results are not sensitive to their exclusion. These results are available upon request.

When stratifying labor markets by occupation groups constructed based on occupation-specific skills, the estimated impact of immigration on native wages is 2-3 times larger than those using education-experience cohorts. The results are robust to changes in occupation classification and controlling for potential selection issues that arise when dealing with occupational choice. Overall, the estimates in section 3.4 suggest a 10% immigrant labor supply shock will decrease native wages by about 5%.

Lastly, we confirm that the impact of immigration on wages is muted when one uses education-experience skill groups. When we estimate the impact of immigration on the wages of demographically comparable natives *within* education-experience groups, the effect is quantitatively similar to those found when using occupation-experience groups. As such, the assumption found in the existing literature—that immigrants and natives are perfect substitutes within education-experience groups—fails to hold.

While the estimates suggest a nontrivial impact on native wages, these are in fact partial equilibrium effects ignoring potential cross-cohort effects of immigration. While immigrants may be perfect substitutes with native within occupation-experience cohorts, they are certainly complements in production to other skill cohorts. Because the degree of complementarity across skill cohorts will have potentially large effects on the general equilibrium effects of immigration on wages, future research should work to include the above into a general equilibrium framework to understand the total wage effect of immigration.

Appendix

A. Creating Manual-to-Communicative Task Index

We use the O*NET database (version 18) to construct the manual-to-communicative task ratio. First, we use select attributes from Ability, Work Activity, Skill, and Knowledge descriptors from the O*NET to create a communicative task-intensity index and a manual task-intensity index. Abilities, Skills, and Knowledge data describe the attributes of workers, while Work Activity describes occupation attributes. For the communicative task-intensity index, we use worker and occupation attributes related to communicating information, social skills, and listening. The manual task-intensity index uses attributes related to basic strength and related characteristics. A full list of attributes for each descriptor used in these calculations (along with their manual/communicative designation) can be found in Table A1 below.

We first compute a measure of overall intensity for each attribute in a given O*NET occupation. The O*NET provides two ratings for the attributes: Importance and Level. The importance rating indicates the importance of a particular attribute to a given occupation, while the level rating indicates the degree to which an attribute is needed to perform a job. We create an overall intensity measure by multiplying Importance (scale 1-5) and Level (scale 1-7). We then normalize each intensity measure to be in the range of 0-1 by dividing by 35.

One limitation of the O*NET is that occupations do not change over time. In order to use these data for my entire sample, we match the occupation groups defined in the O*NET (i.e. 11-1011) to the occupation classification (occ1990dd) of Autor and Dorn (2013). The advantage of the occupation classification of Autor and Dorn (2013) is that occupations are a consistent panel from 1960-2010. To do this, we first match O*NET occupations to occupations defined by the U.S. Census (using the standard crosswalk file and OCC codes from the 2000 Census), then we match the Census OCC codes to the occ1990dd codes (using the files provide by the authors on their website). It should be noted that there are significantly more O*NET occupation groups than occ1990dd occupation groups (841 O*NET vs. 330 occ199dd); thus, there are multiple O*NET occupation groups for each occ1990dd code.

As such, the manual (communicative) task-intensity index for each occ1990dd code is simply the weighted average of all manual (communicative) attribute-specific intensity measures within a given occ1990dd code (weighted by total employment). Then, the manual-to-communicative ratio is calculated by dividing the manual task-intensity index by the communicative task-intensity index.

Table A1: O*NET Components Used in Manual-to-Communicative Ratio

Abilities		
	Verbal (All)	Communicative
	Idea Generation and Reasoning (Fluency of Ideas, Originality, Deductive Reasoning, Inductive Reasoning)	Communicative
	Perceptual (Perceptual Speed)	Communicative
	Sensory (Speech Recognition, Speech Clarity)	Communicative
	Psychomotor (All)	Manual
	Physical (All)	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
Skills		
	Reading Comprehension	Communicative
	Active Listening	Communicative
	Writing	Communicative
	Speaking	Communicative
	Installation	Manual
	Operation Monitoring	Manual
	Equipment Maintenance	Manual
Knowledge		
	English Language	Communicative
	Communications	Communicative
	Building and Construction	Manual
	Mechanical	Manual
1)	Abilities, Work Activities, Skills, and Knowledge are the descriptors	

2)	Within each descriptor, we list all of the "attributes" used in the calculation of the task intensity indices.

B. Sample Description

<u>*B.1 Wage Sample*</u>

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 2010-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.

<u>*B.2 Employment Sample*</u>

To calculate labor supply in each occupation-experience cohort, 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 cohort is the sum of all hours worked. Potential experience is defined as above.

C. Probit Models

<u>*C.1 Labor Supply*</u>

The multinomial probit specifications resemble those in Card (2001). However, to remain consistent with the above, we restrict the sample to males only. We pool the data from 1970, 1980, 1990, 2000, and 2010 and estimate flexible specifications for natives and immigrants separately. The native specification includes the following controls: education, a quartic in potential experience, an indicator variable for being married, a set of race dummies (include Black, Asian, and other non-white), an interaction of education and race dummies, an interaction of education with linear potential experience and quadratic potential experience, and state and year fixed effects. The immigrant specification includes the following controls: education, a quartic in potential experience, a quadratic of years in the U.S, an interaction of education and the quadratic of years in the U.S., 17 country of origin dummies, an interaction of education with three main origin groups (Mexico, Canada/Australia/Europe, and Asia), a set of race dummies (Black, Asian, and other non-white), and state and year fixed effects. We estimate the predicted probabilities of working in occupation *j* for each individual. The predicted labor supply for each occupation is simply the sum of these predicted probabilities.

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