The Labor Market Effects of Competing and Non-Competing High-Skill Immigrants: Evidence from College Majors*

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Abstract

This study uses the college majors of natives and immigrants to separately estimate the labor market effects of competing and non-competing immigrants in the United States. We find that while college-educated immigrants have had small positive effects on employment and no overall effect on earnings, there is significant heterogeneity across native college graduates based on the proportion of competing and non-competing immigrants for each major. We estimate both large negative effects associated with competing immigrants and large positive effects associated with non-competing immigrants. Overall, however, the positive non-competing effects tend to dominate and offset the negative consequences of competing immigrants.

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1 Introduction

The effect of immigrants on the U.S. labor market has received considerable attention in recent policy debates. While the popular press tends to focus on the increased presence of less-educated immigrants in the U.S., a large proportion of foreign-born workers are highly skilled and highly educated. In 2021, 41 percent of foreign-born workers in the U.S. labor force had at least a bachelor's degree (BLS, 2022). As such, foreign-born workers comprise 17 percent of the entire college-educated population. In many large metropolitan areas in the U.S., the percentage of foreign-born college-educated workers is considerably higher. For example, in Miami, Los Angeles, and New York one out of three college-educated workers is foreign born. Moreover, foreign-born workers comprise an even larger proportion of college-educated workers with highly demanded science, technology, engineering, or math (STEM) degrees. In the 40 largest metropolitan areas in the U.S., foreign-born workers comprise 22 percent of all college graduates, but 35 percent of all STEM majors.[1] These differences are even more pronounced for workers with advanced degrees. Immigrants comprise more than half of all U.S. workers with a STEM-based doctorate degree (Kerr and Kerr, 2013; Hanson and Slaughter, 2016). Thus, college-educated immigrants are an important component of the U.S. labor force, particularly high-skill STEM workers.

A long-standing literature in economics examines the impact of immigration on the receiving country and its residents. The literature consistently finds that high-skill immigrants are an important component of domestic innovation and entrepreneurship in the U.S. (Kerr and Lincoln, 2010; Hunt and Gauthier-Loiselle, 2010; Hunt, 2011; Moser et al., 2014; Akcigit et al., 2017; Azoulay et al., 2022; Bernstein et al., 2022). Indeed, there is evidence that high-skill immigrants in the U.S. have enhanced total factor productivity (Peri, Shih, and Sparber; 2015) and boosted per capita economic growth (Hunt, 2017). Despite these positive attributes to the overall economy, concerns remain that high-skill immigration may harm the labor market outcomes of high-skill natives, at least in the short-run. In this regard, the literature contains considerable disagreement: from increasing earnings (Peri et al., 2015; Beerli et al., 2021) to decreasing earnings and employment opportunities of native

[1] Authors' calculations using the 2012-2019 American Community Survey.

high-skill workers (Doran et al., 2022).[2] Moreover, these findings differ from Kerr (2013), an earlier summary of the literature, and Brinatti et al. (2023), a recent working paper, which conclude that high-skill immigrants have limited effects on the labor market outcomes of high-skill natives. While at first glance these different results appear to conflict with one another, this need not be the case. One unifying explanation is that these studies simply differ in the extent to which they focus on similarly skilled natives and immigrants, who are more likely to compete with one another, and differently skilled natives and immigrants, who are less likely to compete with each other (Altonji and Card, 1991).[3] This distinction may be particularly important when analyzing the consequences of high-skill immigration because as Kerr (2013) notes, occupational employment among high-skill workers is broadly fixed due to large differences in skill-requirements across occupations and large investments required to obtain these skills.[4] Indeed, studies that tend to find more negative effects of high-skill immigration tend to focus on very similarly skilled native and foreign-born workers (Borjas, 2005; Borjas and Doran, 2012; Kaestner and Kaushal, 2012; Kerr and Kerr, 2013; Doran et al., 2022).[5] On the other hand, studies that tend to find more positive effects of high-skill immigration tend to focus on less comparable native and foreign-born workers (Peri et al., 2015; Beerli et al., 2021). However, a challenge across all studies is distinguishing between similarly and differently skilled immigrants and natives

This paper uses the college major of natives and immigrants to separately identify inflows of competing and non-competing college-educated immigrants and then estimates how these different immigrant inflows affect the overall labor market outcomes of college-educated natives in the United States. College major is a particularly useful approach to compare immigrants and natives because there is substantial evidence that college majors differ from each other in terms of the skills that they develop (Altonji et al., 2014) and the occupations where they become employed (Altonji et al., 2012). Therefore, an increase in immigrants

[2]While this paper examines on the effects of college-educated immigrants on labor market outcomes, there is an extensive literature examining the impact of less-educated immigrants. Some early and influential papers include: Card (1990), Altonji and Card (1991), and Borjas (2003). Some more recent studies include: Lewis (2011), Foged and Peri (2016), Borjas (2017), Dustmann et al. (2017), and Peri and Yasenov (2019).

[3]Another important explanation in Dustmann et al. (2016) is that the different estimates across the immigration literature stem from the use of different estimation techniques that identify different parameters.

[4]This differs dramatically from low-skill workers who can more easily move between occupations (Peri and Sparber, 2009; Aaronson and Phelan, 2019).

[5]Two important exceptions are Moser et al. (2014) and Friedberg (2001), which find that inflows of highly-skilled immigrants had either complementary or no effects on similarly skilled natives.

with similar college majors to a native worker (i.e. "competing immigrants") could lower wages and possibly harm employment opportunities. However, an increase in immigrants with very different college majors (i.e. "non-competing immigrants") could lead to increases in labor demand for the native worker due to skill complementarities or increases in demand for local services. In this regard, college major provides a natural structure to think about the ways in which inflows of high-skill foreigner-born workers could compete with some natives (i.e. those with a similar college major) and not compete with others (those with a very different major).

College major is arguably a better way to compare similarly-skilled natives and foreign-born workers than occupations, which have been used extensively in the immigration literature (Card, 2001; Orrenius and Zavodny, 2007; Kerr and Lincoln, 2010; Peri and Sparber, 2011; Bound et al., 2015; Peri et al., 2015), because college major is a fixed pre-labor market characteristic. Occupational employment, however, is endogenous since native workers can quickly migrate out of competing occupations precisely because of an increase in foreign-born workers (Peri and Sparber, 2009; Kerr and Kerr, 2013; Cattaneo et al., 2015; Lin, 2019; Ma, 2020). Moreover, there is extensive empirical evidence that immigrants downgrade their occupational employment upon arriving in their host country (Dustmann et al., 2016). While these individuals are underemployed, they may still impose competitive pressure on employment outcomes in their desired occupation even if they are employed elsewhere. An occupation-based analysis will miss both of these effects and bias estimates. Another concern with performing an occupation-based immigration analysis is simply that human capital may be broader than occupation-specific. A recent economics PhD, for example, could easily find herself employed in a range of occupations including professor, consultant, or data scientist. In this way, an individual's skills can be valued in many occupations and their employment outcomes will then be a function of the overall supply and demand for these skills across the entire labor market. Indeed, many academic economists argue that they deserve higher salaries, compared to other academics, precisely because the value of their outside option in consulting or tech is so high. An occupation-based analysis would miss these broader dimensions to skills while a college-major based analysis would better pick up these across-occupation spillovers.

Importantly, college major is not without its own endogeneity concerns. There is some evidence that the presence of foreign-born STEM majors suppresses the likelihood that native students major in STEM fields (Orrenius and Zavodny, 2015; Anelli et al., 2017; Ransom and Winters, 2021). However, given the time necessary to complete a college degree, this labor supply response is unlikely to affect labor market outcomes in the short or even medium run. Therefore, while college major is not a perfect solution, it arguably has more advantages and fewer problems than using occupations.

There are two other studies that we are aware of that also use college major to analyze the effects of high-skill immigrants on the labor market outcomes of high-skill natives (Ransom and Winters, 2021; Turner, 2022).[6] This paper improves upon those studies by using college major to identify and estimate the effects of both competing and non-competing high-skill immigrants, whereas these two previous studies simply use college major to estimate the effects of competing immigrants. This exclusion of non-competing immigrants could prove consequential if the effects of non-competing immigrants are non-trivial. For example, Turner (2022) finds that inflows of immigrant STEM majors lower the earnings of native STEM majors relative to non-STEM majors. However, this change in relative earnings could come from either decreasing the earnings of native STEM workers (a competing effect) or increasing the earnings of native non-STEM workers (a non-competing effect). Clearly, the mechanism leading to this relative change is important for assessing the desirability of immigration. In this way, our analysis allows us to better assess the potential benefits of immigration on native workers. It also allows us to better understand heterogeneity in outcomes associated with inflows of college-educated immigrants (Dustmann et al., 2013).

Using the sample of college graduates living in the 40 largest metropolitan areas in the U.S. from the 2012-2019 American Community Survey (ACS), we develop metrics of competing and non-competing immigrants using an index of congruence, which describes the similarity of occupational employment between natives and immigrants based upon their college major. We then estimate how inflows of college-educated immigrants in one's metropolitan area affect the earnings and employment probabilities of college-educated natives, where we distinguish between effects associated with inflows of all immigrants, inflows of competing immigrants, and inflows of non-competing immigrants. Our empirical approach follows the Dustmann et al. (2016) "pure spatial approach" and identifies the total

[6] Ransom and Winters (2021) examine how exposure to foreign STEM workers affects native college graduates. They find some evidence of deleterious effects: discouraging black men from majoring in STEM, changing the occupational employment of male STEM majors, and lowering employment probabilities for female STEM majors.

effect of these inflows. These expressions are estimated using instrumental variables where we use the immigrant enclave instrument (Altonji and Card, 1991) to control for the endogenous sorting of immigrants.

We find that inflows of college-educated immigrants into the U.S. during the 2010's led to small and marginally significant increases in overall employment but no meaningful effects on full-time employment or earnings. However, these null effects mask important heterogeneity by college major where inflows of competing immigrants decrease earnings and full-time employment opportunities of native college graduates but inflows of non-competing immigrants increase earnings and (full and part-time) employment opportunities. The net effect of these offsetting impacts varies across college majors but is largely positive because (i) all native college graduates are exposed to both competing and non-competing immigrants and (ii) most immigrants during our period of analysis are non-competing. Native education and health majors have particularly benefitted from college-educated immigration over this period due to smaller inflows of competing immigrants and larger inflows of non-competing STEM immigrants. The estimates also imply a great deal of heterogeneity at the major-by-MSA level because the inflow rates of immigrants and the composition of those immigrants – competing vs. non-competing – vary at the major-by-MSA level. Indeed, we find that the MSAs that experienced the largest immigrant inflows experienced both the largest average gains (because most immigrants are non-competing) and the largest within-MSA variation in outcomes across majors. Thus, our estimates uncover substantial heterogeneity in the effects of college-educated immigrants across majors and MSAs. Moreover, we show that an occupation-based analysis misses most of this variation as it conflates both the competing and non-competing effects of immigration.

Lastly, we examine heterogeneity in these effects across demographic groups and industries to better understand the distributional consequences and underlying causes of these effects. We find that younger natives tend to experience larger negative effects associated with inflows of competing immigrants, but also larger positive effects associated with inflows of non-competing immigrants. Thus, both the costs and benefits of college-educated immigration are concentrated among younger native workers. We also explore industry-level variation in our estimates to better understand the underlying cause of the sizeable non-competing effects that we estimate. Our results suggests that skill complementarities likely explain the positive non-competing effects we estimate.

Our analysis makes important contributions to the immigration literature unifying the seemingly disparate findings that college-educated immigrants sometimes harm native labor market outcomes while at other times improve outcomes. Indeed, we show that the same immigrant, for example an immigrant computer science major, will hurt employment opportunities for natives with competing college majors (e.g. native computer science majors) but bestow substantial benefits on natives with non-competing majors, such as native education majors. In this way, college-educated immigration could create winners and losers among native workers (Price et al., 2020). However, during our period of analysis new college-educated immigrants have largely improved native labor market outcomes because immigrants have largely been non-competing. Thus, our analysis highlights that it is not the quantity of college-educated immigrant inflows that affects native labor market outcomes, but rather the skill mix of natives and immigrants in the local area.

2 Theoretical Framework

We use a Rosen—Roback model (Rosen, 1979; Roback, 1982) of local labor markets with many of the extensions from (Moretti, 2011) to better understand the regional labor market implications of inflows of immigrants with different skills. The model highlights the ways in which inflows of similarly and differently skilled immigrants may help and/or harm native workers. The implications of the model are somewhat similar to Altonji and Card (1991), but the model extensions, which include a non-tradable sector and agglomeration effects, highlight additional ways that immigration could benefit native workers.

2.1 Baseline Model

Following Moretti (2011), suppose that an individual's utility from living in a city is a function of the city-specific wage, the aggregate amenity value of residing in the city, and an idiosyncratic component to the amenity value. In the simplest model, there are two cities (a and b), labor is homogeneous, mobility between cities is costless, and each individual supplies one unit of labor. Then, an equilibrium is a wage in each city such that the marginal worker is indifferent between residing in a or b. If a worker's relative preferences between a and b are uniformly distributed, then the local labor supply curve is upward sloping – with stronger idiosyncratic preferences for locations associated with an inelastic labor supply curve (Moretti, 2011). Further, if all firms produce a single internationally traded good and output is a constant returns to scale function of the number of workers and an exogenous city-specific productivity effect, then the labor demand curve is downward sloping.

In this simple framework, an exogenous increase in the labor supply into one city due to an influx of immigrants from a foreign country will harm natives in both cities as wages fall in both places. The intuition of this result is a straight-forward application of the supply and demand framework. Immigrants moving into city b increase labor supply causing wages in b to fall because the labor demand curve is downward sloping. As wages fall, workers move from city b to city a causing a similar supply shock in city a, which decreases wages accordingly. Despite this parallel response in a, it is important to note that the decrease in wages in b, the city that experienced the immigration shock, will be larger than the decrease in city a wages. This comes from the fact that mobility is not perfect, i.e. only the marginal worker is indifferent between the two cities in equilibrium (Moretti, 2011) and all others receive premiums from living and working in b. Thus, in this set-up, immigration into one city harms workers in both cities, but disproportionately harms the workers in the receiving city. There is some debate about the magnitudes of these spillover effects across cities with some studies suggesting they are large (Borjas, 2006) while others suggest they are quite small (Glaeser, 2008; Notowidigdo, 2020). Either way, the potential for spillovers across geographic areas implies that some caution is warranted in city-by-city empirical analyses of immigrant inflows.

The implications of this baseline model, however, are limited in their applicability because the assumptions of the model are too restrictive, especially in the context of high-skill college-educated immigration where (i) the skills of college-educated workers are likely to be quite varied as skills developed across college majors are very different (Altonji et al., 2014), (ii) the vast majority of college-educated workers are employed in the non-tradable service sector, and (iii) the increased presence of highly-skilled workers could be associated with positive agglomeration effects. Thus, we consider three important extensions to better model the labor market consequences of high-skill immigration.

2.2 Extensions

2.2.1 Skill Heterogeneity

Suppose now that there are two types of workers, STEM workers and non-STEM workers, where worker type is exogenous. Suppose as well that firms use both types of labor in production and the two types of labor are gross complements. If all other assumptions of the model are the same, the equilibrium condition is similar to the baseline model: the marginal worker of each type must be indifferent between locating in city a or city b.

Immigration of one type of worker (e.g. STEM workers) into one city will cause heterogeneous effects on the native population in that city, with native STEM workers experiencing falling wages (due to the increase in the supply of competing workers) and native non-STEM workers experiencing wage gains (due to rising marginal productivity from the increase in non-competing/complementary workers). Like the baseline model, the effects of immigration into one city spillover symmetrically to the other city, but the effects are again largest in the city that experienced the immigration inflow because of imperfect mobility. If immigrants are composed of both types of workers (but a majority are STEM workers), the positive and negative effects on non-STEM and STEM natives will be more muted – both smaller positive effects on non-STEM workers and smaller negative effects on STEM workers. Thus, natives of any given type will benefit more the larger the proportion of immigrants that are non-competing, as opposed to competing.

2.2.2 Non-Tradable Sector

Another relevant extension is to add a locally produced non-tradable service good to the economy. Abstracting from the sectoral allocation problem for workers, the key implication of this extension is that it implies that an increase in the local population (due to immigration or any reason) will increase the demand for the locally produced service good and thus, increase the local labor demand for workers in this sector. If the non-tradable sector employs both types of labor, then this increase in demand for the service good will increase wages for both STEM and non-STEM workers – offsetting some of the native STEM wage losses associated with immigration (assuming immigrants are largely STEM workers) and enhancing non-STEM wage gains.[7] Therefore, a robust service sector will cushion the labor market experiences associated with immigration. This channel may be particularly important in the U.S. because high-skill locally produced services in health care and education are a large component of U.S. GDP.[8]

2.2.3 Agglomeration Effects

One final extension is to add agglomeration effects – where increases in number of workers of a particular type in a particular city increase the productivity of that type in the city, increasing labor demand. This extension could again be important in the U.S. context because high-skill immigrants have been an important component of innovation and entrepreneurship (Hunt and Gauthier-Loiselle, 2010), making immigrants job creators (Azoulay et al., 2022). If these effects are present, then the wage declines associated with inflows of competing immigrants would be further weakened. At the same time, agglomeration effects would also strengthen the non-competing effects via either the skill complementarity or increased demand for local services channel. Thus, agglomeration effects improve the labor market outcomes for all natives.

2.3 Model Implications for Empirical Work

The Rosen—Roback model and its extensions highlight three important implications about the labor market effects of high-skill immigration. First, the regional reallocation of native workers responding to inflows of immigrants could bias city-by-city estimates of the impact of immigration. Thus, it is important that empirical analyses associated with inflows of college-educated immigrants test whether regional reallocation of native workers is taking place. Second, the model implies that the effects are quite likely to be heterogeneous across the population with competing workers (i.e. natives with skills most-similar to the newly arriving immigrants) more likely to experience more negative effects and non-competing

[7]Notably, the increased demand for the service good could benefit non-STEM workers more than STEM if the service sector uses more non-STEM workers.

[8]The spillover effects into city a when the model is extended to include a service sector are again evident in this extension and will mirror the primary effect in city b. This comes from the decrease in the supply of workers in b as they move to a to gain employment in the service sector. However, the spillover effects are slightly complicated by the fact that the increase in demand for local services in a will also change the price for the service good in both a and b. Thus, nominal wage effects will differ from real wage effects in this extension.

workers more likely to experience more positive effects. Thus, it is essential that empirical analyses examining the labor market effects of high-skill immigration properly distinguish between inflows of competing and non-competing immigrants as the average effect across all college-educated workers likely masks significant heterogeneity across the native population. And third, the model implies that the positive effects of immigration can come from two distinct sources (separate from agglomeration): skill complementarities in production or increased demand for locally produced service goods. To the extent possible, empirical studies should try to assess the relative importance of these two channels as they shed further light on the distributional consequences of immigration.

3 Data

3.1 American Community Survey

The primary data we use in the empirical analysis are from the 2012-2019 American Community Survey (ACS). The ACS is a cross-sectional national survey of about 3 million individuals in the U.S. that has been undertaken annually by the U.S. Census Bureau since 2005. The survey asks respondents about their demographics, labor market experience, country of birth, and year of arrival in the U.S. (if foreign-born). Since 2009, the ACS has also asked respondents with a college degree about their undergraduate college major – regardless of their country of birth. College major is particularly useful information because it allows us to distinguish between college-educated immigrants and the native sample, better assessing who competes with whom. These questions, combined with the large sample size make the ACS an excellent data source to analyze the heterogeneous effects of college-educated immigration on native labor market outcomes.

We focus our analysis on college-educated respondents aged 25 to 60 who live in one of the 40 most-populous metropolitan areas in the United States. This focus on respondents in large metropolitan areas (MSA) is necessary because we use the MSA to represent the local labor market wherein natives and immigrants compete for jobs. The 40 largest MSAs have enough observations of both natives and immigrants to reasonably measure inflow rates of college-educated immigrants at the college-major level.[9] However, it is not feasible to compute these inflow rates for each of the 171 individual majors coded in the ACS. Thus, we combine the 171 unique majors into seven aggregated college majors, which include: (1) business; (2) computer science and math; (3) engineering; (4) science; (5) health; (6) education, and (7) liberal arts. This aggregation is similar to the aggregation of college majors in Sjoquist and Winters (2015), Kirkeboen et al. (2016), Phelan and Sander (2017). We later show that our results are not overly sensitive to changes in the largest of these aggregated majors, i.e. business and liberal arts.[10] The specific college majors included in each aggregated major are presented in Appendix Table A1.

We start our analysis in 2012 because the U.S. Census Bureau made large changes to MSA boundaries beginning in 2012 and it is not possible to develop consistent geographic areas using the earlier definitions without scaling up the size of the local labor market significantly.[11] We end the analysis in 2019 to avoid complications associated with the Covid-19 pandemic. Once we pool the 2012-2019 ACS surveys, we have a sample of a little over 2.2 million college graduates aged 25-60 who are not currently enrolled in school. We present summary statistics on the 900,023 observations from the 2017-2019 period in Table 1. We focus on these three years because these are the years for which we can construct five-year changes in average labor market outcomes (2012-2017, 2013-2018, and 2014-2019), the dependent variable in our empirical analysis.

As shown in Table 1, more than one fifth of our sample (22.1 percent) is foreign-born. In many respects – such as age, sex, earnings of full-time workers, and hours worked for full-time workers – the native and immigrant samples are quite similar.[12] However, the samples

[9] We chose this specific cutoff because the number of immigrants coming into an MSA and into a major within an MSA drop significantly after the top 40 MSAs. For example, the average number of aged 25-60 college-educated immigrants entering an MSA ranked 41-50 in the ACS data is 48 per year compared to 140 per year for an MSA ranked 31-40. This reduces the average number of immigrants within each aggregated major from 20 to 7 and within the smallest majors such as education and health, from 5 to 2. The 40 most-populous metropolitan areas are based on 2010 MSA-level populations from the IPUMs "Crosswalk Between 2013 MSAs and 2010 PUMAs" available online at https://usa.ipums.org/usa-action/variables/MET2013#description_section, last accessed December 29, 2022.

[10] Business includes accounting, economics, finance, marketing, management, and general business. Liberal arts includes the humanities, the fine arts, the social sciences (other than economics), and communications.

[11] Another benefit of starting in 2012 as opposed to 2009 is that we avoid analyzing the first few years following 2007/2008 financial crisis.

[12] A full-time worker is defined as someone who worked at least 48 weeks over the past year, averaged at least 30 hours of work per week worked, and was paid an hourly rate at least as large as the minimum wage.

differ in terms of their college major, their probability of having a graduate degree, and their probabilities of employment. The native-born sample is more likely to be employed and employed full-time, but less likely to have a graduate degree than the immigrant sample – especially immigrants that arrived in the U.S. aged 20 or older. We make this distinction, immigrants arriving before age 20 and aged 20 or older, because we do not observe whether immigrants in the ACS are educated abroad or not. Thus, we use age of arrival to proxy a sample likely to be educated abroad. Not surprisingly, immigrants that arrived in the U.S. as children, see column (f), look more similar to the native population than those that arrived as adults, see column (g). Thus, our main empirical analysis uses inflows of immigrants aged 25-60 that arrived as adults (i.e. aged 20+) over the previous five years. Summary statistics on this sample are presented in column (h) of Table 1.

Natives and immigrants also differ in their college major. Native-born college graduates are much more likely to be education or liberal arts majors (47 percent for natives vs. 26 percent for immigrants) and less likely to be STEM majors (21 percent for natives vs. 44 percent for immigrants) than recent-arriving adult immigrants. These differences are even more pronounced when comparing native women and immigrants, with native women even more likely to major in liberal arts or education (55 percent) and even less likely to major in STEM (14 percent). Notably, these differences in the proportion of STEM majors are largely due to differences in engineering and computer science (and not science).

3.1.1 College Major and Occupational Employment

Much of the empirical analysis in this paper builds off the findings in the economics literature on college major, which show that workers with the same college majors are more likely to develop the same skills (Altonji et al., 2014) and more likely to work in the same occupations (Altonji et al., 2012). These findings suggest that natives and immigrants with the same college major may be more likely to compete with each other for the same jobs while natives and immigrants with very different college majors may be more likely to work in different occupations, making them less likely to compete with each other.[13] However, it is instructive to use the ACS to examine if this is indeed true since immigrants may face labor

[13]This focus on the similarity and differences in occupational employment is important for determining the degree of competition between natives and foreign-born workers because some component of human capital is occupation-specific (Kambourov and Manovskii, 2009; Gathmann and Schönberg, 2010).

market difficulties upon arrival in their new country (Lubotsky, 2007; Oreopoulos, 2011), which could prevent college major from being as relevant when comparing immigrants and natives.

Figure 1 plots employment by two-digit occupation for different college majors using the full sample (natives and immigrants) of employed aged 25-60 college graduates in the ACS.[14] The data suggest that most college majors become employed in occupations that match their college major. For example, about 70 percent of business majors are employed in management occupations or business, finance, and sales occupations. Similarly, almost 60 percent of education majors are employed in education occupations and about 70 percent of health majors are employed in health occupations. STEM majors also tend to work in STEM-related occupations, but their employment is somewhat more dispersed across occupations than other majors. About 45 percent of computer science and math majors work in computer science or math occupations; 45 percent of engineering majors work in engineering occupations or computer science/math occupations; and 45 percent of science majors work in science occupations or health occupations. Figure 2 is similar to Figure 1, but it breaks out employment separately for natives and immigrants. Interestingly, the distribution of occupational employment for foreign-born college graduates by college major is very similar to the native sample – with immigrants only slightly less likely to work in an occupation most closely aligned with their college major. Thus, at first glance, native and immigrant college graduates both tend to concentrate their employment in occupations directly related to their major.[15]

To further assess which natives and immigrants are competing with each other for occupational employment (and which are not), we compute an index of congruence, used by Welch (1999) and adapted to the immigration literation in Borjas (2003). The index of congruence, $G_{m_n m_f}$, is a statistic, which describes the similarity of occupational employment between two groups. Like a correlation coefficient, all index of congruence values sit on the $[-1, 1]$ interval. A value of one implies that the distribution of occupational employment is identical between the two groups while a value of negative one implies full occupational

[14]We make some minor adjustments to the two-digit occupation codes, which are described in the notes to Figure 1, but these adjustments do not affect the employment shares within occupations presented in Figure 1.

[15]A notable exception is Liberal Arts majors, who are missing from both Figure 1 and Figure 2. Generally speaking, their employment is more dispersed across occupations. This point is discussed in more detail below.

segregation. Specifically, we compute the following index of congruence ($G_{m_n m_f}$) between natives (n) and immigrants (f) with majors m_n and m_f, respectively, as:

$$G_{m_n m_f} = \frac{\sum_o \frac{(q_{m_n o} - \bar{q_o})(q_{m_f o} - \bar{q_o})}{\bar{q_o}}}{\sqrt{(\sum_o \frac{(q_{m_n o} - \bar{q_o})^2}{\bar{q_o}})(\sum_o \frac{(q_{m_f o} - \bar{q_o})^2}{\bar{q_o}})}}$$

where $q_{m_n o}$ is the fraction of natives (n) with college major m_n employed in occupation o, $q_{m_f o}$ is the fraction of immigrants (f) with college major m_f employed in occupation o, and $\bar{q_o}$ is the employment share in occupation o across the entire college-educated population. Occupations are measured using the 490 four-digit census occupation codes and the sample is limited to employed college-educated individuals.

Table 2 presents the index of congruence (IOC) values for native and immigrant college graduates. The rows represent the college majors of native college graduates and the columns represent the college majors of immigrants. Looking across the first row, the IOC values show how immigrants with different college majors match the occupational employment of native business majors. The IOC values imply that native business majors are employed in very similar occupations as immigrant business majors with an IOC value of 0.73. Moving across the row, the IOC values also imply that native business majors tend to work in different occupations than all other immigrant college graduates – with negative IOC values for all other majors.

Two clear patterns emerge from the IOC values. First, natives and immigrants with the same college major tend to work in very similar occupations. These IOC values, located on the diagonal of Table 2, are the largest value in each row and average 0.76 across all majors. Second, a great majority of the IOC values for native and immigrants with different college majors are negative. Thus, the IOC values imply that most natives and immigrants with different majors largely work in different occupations and hence, do not directly compete with each other for jobs. That said, there are two notable exceptions. Native computer science majors tend to work in similar occupations as immigrant engineering majors with an IOC value of 0.55 and native science majors appear to work in similar occupations as immigrant health majors with an IOC of 0.22. Therefore, we include these additional two native/immigrant college major matches in our definition of competing immigrants (along with natives and immigrants with the same major). We define all other immigrant/native major combinations as non-competing. This amounts to the following rule. If $G_{m_n m_f} > 0.20$ then two occupations are "competing" for similar employment. Otherwise, they are "non-competing." This cutoff ensures that each major has a unique set of competing and non-competing majors. However, we also perform robustness tests to test the sensitivity of our results to this definition including: increasing the cutoff to 0.53 (the smallest IOC for immigrants and natives with the same major) and decreasing the cutoff to 0.

One complicating factor is how to handle double majors. For example, some natives may double major in history and engineering. For this individual, does this mean that they face more competing immigrants (i.e. competing immigrants for both engineering and liberal arts majors) or more non-competing immigrants (i.e. non-competing immigrants for both majors)? To avoid this complication, we exclude all native double majors (10.8 percent of observations) from our main sample. Later, however, we present robustness estimates where we add this sample back in and use all native college graduates.[16]

3.1.2 Immigrant Inflows

In our empirical analysis, we evaluate the labor market effects of inflows of all college educated immigrants (at the MSA level) and then all competing and non-competing college-educated immigrants (at the MSA-by-major level). These inflow rates reflect the number of aged 25-60 adult college-educated immigrants that arrived in an MSA over the previous five years divided by the total number of aged 25-60 college graduates residing in that MSA five years prior. Thus, the inflow rate of all immigrants into MSA c in year t ($InflowFB_{ct}$) is:

$$InflowFB_{ct} = \frac{\sum_i NewImm_{ict}}{\sum_i ColEdu_{ic,t-5}}$$

where $NewImm_{ict}$ is an indicator if individual i is an aged 25-60 college-educated immigrant that arrived into MSA c within the last five years of year t,[17] $ColEdu_{ic,t-5}$ is an indicator

[16] When we include native double majors in our analysis, we simply use their first reported college major as their major and determine the inflows of competing and non-competing immigrants accordingly. For newly arriving immigrants, we always include immigrant double majors (8.3 percent of the sample) to compute our immigrant inflows and we assign immigrant double majors to their first reported major.

[17] We define $NewImm_{ict}$ using the year of entry variable in the ACS ("YOEP"), which they ask of all individuals born outside the US. Thus, a newly arriving immigrant into MSA c in 2017 is an aged 25-60 college-educated person in c who reports being foreign born (NATIVITY=2) and whose year of arrival in the US is sometime between 2012-2017. By definition, then, the age at arrival for this sample would have to be aged twenty or older, which largely limits the analysis to individuals educated abroad.

if individual i is an aged 25-60 college graduate in c from the ACS sample five years prior to year t, and both are summed across all individuals in an MSA/year in the ACS. Sample weights are used to ensure that these inflow shares are representative of the MSA.

The overall inflow rate can then be decomposed into inflows of competing and non-competing immigrants for each major. The inflow rate of competing immigrants ($InflowFB_{cmt}^{Comp}$) for major m in MSA c and year t is:

$$InflowFB_{cmt}^{Comp} = \frac{\sum_i (I_{im} * NewImm_{ict})}{\sum_i ColEdu_{ic,t-5}},$$

where I_{im} is an indicator if individual i has a competing major for a native with major m,[18] and we again sum $I_{im} * NewImm_{ict}$ and $ColEdu_{ic,t-5}$ across all individuals using the sample weights to ensure that the inflow shares are representative. Since I_{im} is a unique set of immigrant majors for each native major, the inflow rate of competing immigrants varies at the major-by-MSA-by-year level. We then define the inflow rate of non-competing immigrants ($InflowFB_{cmt}^{NComp}$) as:

$$InflowFB_{cmt}^{NComp} = InflowFB_{ct} - InflowFB_{cmt}^{Comp},$$

which also varies at the major-by-MSA-by-year level.

Given these definitions, there is substantial MSA-level variation in the inflow rates of recent arriving college-educated immigrants. For example, the inflow rate of all college-educated immigrants ($InflowFB_{ct}$) averaged 2.4 and 2.8 percent in Denver, CO and Minneapolis, MN over the periods 2012-2017, 2013-2018, and 2014-2019. However, inflows averaged 11.4 percent and 14.8 percent in Miami, FL and San Jose, CA, respectively, over the same years. There is also significant variation in inflow rates of competing majors ($InflowFB_{cmt}^{Comp}$) across MSAs within a major. For example, the inflow rate of new immigrant engineering majors (which compete with native engineering majors and native computer science majors) averaged 0.8 percent in Chicago but 2.5 percent in Seattle and

[18] Given the $G_{m_n m_f} > 0.20$ definition, the competing majors for native business majors are foreign-born business majors; for native engineering majors are immigrant engineering majors; for native computer science majors are immigrant computer science and immigrant engineering majors; for native science majors are immigrant science and immigrant health majors; for native health majors are immigrant health majors; for native education majors are immigrant education majors; and for native liberal arts majors are immigrant liberal arts majors.

5.8 percent in San Jose. Lastly, these inflow rates of competing immigrants also vary across majors within an MSA. Of the 14.8 percent inflow rate of immigrants arriving into San Jose, 5.8 percent are engineering, 3.7 percent are computer science, 2.1 percent are business, 1.5 percent are liberal arts, 1.0 percent are science, and both health and education majors account for less than one-half of one percent.[19] These examples are not unique. As we show in Appendix Table A2, there is a great deal of variation in overall inflows across MSAs and inflows of competing and non-competing immigrants at the MSA-by-major level.

3.2 1990 and 2000 Decennial Census

We also use data from the 1990 and 2000 Decennial Census to construct our instruments for the immigrant inflow variables. Specifically, we use these data sources to construct the pre-existing settlement patterns of earlier arriving immigrants based on their country of origin. The specific instruments are discussed in more detail below.

4 Empirical Approach

The empirical analysis uses MSA-level variation in the inflows of college-educated immigrants to examine the impact of college-educated immigrants on the labor market outcomes of native college graduates in the U.S. Different from other empirical analyses, we use the college majors of natives and immigrants to separately identify the effects of inflows of both competing and non-competing college-educated immigrants.

4.1 Basic Set-up

Suppose that the average labor market outcome for workers in MSA c and major m in year t (Y_{cmt}) is a function of MSA-specific effects (α_c), time-specific college major effects (α_{mt}), the proportion of college-educated workers that are immigrants ($ShFB_{ct}$), and an error term

[19] Of course, inflows of competing immigrants are not the same as inflows of immigrants with the same major for native computer science and science majors where inflows of competing immigrants for native computer science majors is the sum of inflow rates of immigrant computer science and engineering majors and inflows of competing immigrants for native science majors is the sum of inflow rates of immigrant science and health majors.

(ϵ_{cmt}); which we express as:

$$Y_{cmt} = \alpha_c + \alpha_{mt} + \beta_1 ShFB_{ct} + \epsilon_{cmt}.$$

To better understand the medium-run impact of college-educated immigrants on native labor market outcomes, we take five-year differences of the above expression. Thus, we estimate:

$$\Delta Y_{cmt} = \alpha_{m\Delta t} + \beta_1 InflowFB_{ct} + \epsilon_{cm\Delta t}. \tag{1}$$

where $\Delta Y_{cmt} = Y_{cmt}–Y_{cm,t-5}$ is the change in the average labor market outcome for individuals with major m in MSA c from five years prior,[20] $\alpha_{m\Delta t}$ are major-by-year fixed effects, and $InflowFB_{ct}$ is the change in the proportion of college educated immigrants.[21] Then, β_1 is the difference-in-difference estimator describing the impact of inflows of college-educated immigrants using variation across MSAs and time. This approach, which Dustmann et al. (2016) refer to as the pure spatial approach, identifies the average total effect of college-educated immigrant inflows on native labor market outcomes (across majors).

We then extend Equation 1 to separately estimate the effects of inflows of competing and non-competing immigrants. As we showed earlier, the total inflow of college-educated immigrants can be broken up into inflows of competing and non-competing immigrants, with $InflowFB_{ct} = InflowFB^{Comp}_{cmt} + InflowFB^{NComp}_{cmt}$. Substituting this expression into Equation 1, it becomes:

$$\Delta Y_{cmt} = \alpha_{m\Delta t} + \beta_1 (InflowFB^{Comp}_{cmt} + InflowFB^{NComp}_{cmt}) + \epsilon_{cm\Delta t}.$$

[20] ΔY_{cmt} is constructed by first taking the average outcome for natives with major m in MSA c in each year of the ACS. Then, these values are differenced over time. For example, $\Delta Y_{cm,2017} = Y_{cm,2017} - Y_{cm,2012}$.

[21] As we describe in fn. 17, we compute the inflow rate using the "yesr of arrival" in the U.S. variable from the ACS. This approach to measuring new immigrants into c differs from other approaches, which use the change in the total number of immigrants between 2012 and 2017. We opt for this approach because when we compute inflow rates of competing and non-competing immigrants (which vary at the MSA and college major level), some inflows become quite small. For example, the number of new immigrant education majors into Pittsburgh in 2017 is three. Thus, the more-traditional approach would create additional noise in our inflow rate variables due to imprecise estimates of immigrants in both the current year and base year. That said, we present robustness estimates later in the paper that use this latter approach to compute the inflow rate. As we discuss then, these two immigrant inflow measures are highly correlated and thus, the estimates are not significantly affected by this choice.

However, there is no reason to think that inflows of competing and non-competing immigrants will have the same effect on native labor market outcomes. Thus, we instead estimate:

$$\Delta Y_{cmt} = \alpha_{m\Delta t} + \beta_2 InflowFB_{cmt}^{Comp} + \beta_3 InflowFB_{cmt}^{NComp} + \epsilon_{cm\Delta t}, \tag{2}$$

where β_2 captures the total effect of inflows of competing immigrants and β_3 captures the total effect of inflows of non-competing immigrants. Since the inflows of competing and non-competing immigrants differ by major, the predicted effect of the immigrant inflows on labor market outcomes will also differ by major within (and across) MSAs. Thus, while β_1 from Equation 1 can be used to predict the average effect of college-educated immigrant inflows on natives within an MSA, the β_2 and β_3 coefficients from Equation 2 can be used to predict average effects on natives at the MSA-by-major level. Thus, the estimates of Equation 2 unpack the average effects implied by Equation 1 and allow us to analyze heterogeneity.

The specific labor market outcomes (ΔY_{cmt}) that we examine include: the change in the natural log of total native college majors, the change in the employment rate, the change in the full-time employment rate,[22] and three different measures of the change in the natural log of average earnings (including zeros, excluding zeros but including all positive earnings, and limiting the sample to full-time employed workers).[23] These outcomes allow us to assess whether immigration is inducing native outmigration, affecting native employment, and affecting native earnings. The β-coefficients in all expressions represent elasticity coefficients. Standard errors are clustered at MSA-level.

4.2 Identification

A common concern with estimating Equation 1 and 2 is that immigrant inflows are likely correlated with time varying factors affecting changes in native labor market outcomes, such as changes in labor demand (Llull, 2018). Thus, estimates of Equation 1 and 2 using OLS

[22]Full-time employment is defined as working at least 48 weeks in the past year, averaging at least 30 hours per week during that time, and being paid an hourly rate of at least the minimum wage.

[23]The ACS top-codes the earnings levels of the top three percent of earners within each state in each year and replaces these individual earnings with the average earnings across all top-coded earners in the state/year. To compute average earnings for a specific major-by-MSA in a particular year, we exclude top-coded earnings values because the distribution of college majors among top-coded earnings values need not be uniform. Their inclusion could cause us to overstate the average earnings of some majors and understate the average earnings of others.

are likely to be biased. To address the non-random sorting of college-educated immigrants to MSAs, we estimate Equation 1 and 2 using instrumental variables. We follow the lead of Altonji and Card (1991), Card (2001), Dustmann and Glitz (2015), Tabellini (2020), and many others and use the immigrant-enclave instrument to instrument for the immigrant inflows. This instrument, a version of the shift-share instrument (Bartik, 1991), assumes that new immigrants place a non-pecuniary value of being in the same geographic areas as previous immigrants from the same home country. Thus, past settlement patterns push new immigrants to geographic areas unrelated to local labor demand conditions (Card, 2001). This approach identifies the local average treatment effect associated with the population induced to locate to geographic areas because of these push factors (Cornelissen et al., 2016).

The immigrant enclave instrument for the inflow of all immigrant college-graduates from Equation 1 is captured by the following expression:

$$Z_{InflowFB_{ct}} = \frac{\sum_j [\lambda_j^{c,t=0} (\sum_i NewImm_{ijt})]}{\sum_i ColEdu_{ic,t-5}},$$

where $NewImm_{ijt}$ is an indicator for whether individual i is an immigrant from country j that arrived in the past five years (relative to t), $\sum_i NewImm_{ijt}$ is the total inflow of recently arriving college-educated immigrants from country j (i.e. "the shift") in year t, and $\lambda_j^{c,t=0}$ is the "the share" variable, capturing the share of immigrants from country j living in c from an earlier-arriving immigrant cohort ($t = 0$). The share variable assigns new immigrants from home country j probabilistically to MSAs across the U.S. based upon the prior location decisions of earlier arriving immigrants from j.[24]

The pre-existing settlement pattern variable, $\lambda_j^{c,t=0}$, can be constructed in several ways. One important question is: which immigrants should be included to compute $\lambda_j^{c,t=0}$? In this regard, the literature has sometimes used immigrants with similar skills to the immigrants examined (Kerr and Lincoln, 2010; Kerr et al., 2015; Peri et al., 2015). Thus, we could construct $\lambda_j^{c,t=0}$ using solely college-educated immigrants. Unfortunately, however, we cannot use immigrants with the same college major to construct major-specific λ's because we do not have historical data on the past settlement patterns of immigrants by college major.

[24] The specific countries j that we use to construct our instruments include: China, Cuba, India (including Pakistan), Mexico, the Philippines, and the UK (including Australian, Canada, and Ireland). Most other countries are aggregated to the continent level and include: Africa, Central/South America, Eastern Europe, Western Europe, and Asia. The aggregation is similar, but slightly more aggregated than Card (2001).

Another outstanding question is: how far back should one go to establish the pre-existing settlement patterns of earlier arriving immigrants, i.e. what period should constitute $t = 0$? Earlier periods are more likely to be exogenous but may also be less predictive of migration patterns (Butcher et al., 2022; Furtado and Ortega, 2023) and thus, create weak instrument problems. This ambiguity led us to construct several different λ's using different data sources (both the 2000 Decennial Census and the 1990 Decennial Census) and different samples of immigrants in those surveys (all aged 25-60 immigrants and all aged 25-60 immigrants with a college degree). While our primary estimates use college-educated immigrants from the 2000 Census to construct our instruments, we present estimates using all four samples to test the sensitivity of our results to the sample used to construct the λ's.

The instruments for inflows of competing and non-competing immigrants are constructed similarly, where the instrument for inflows of competing immigrants is:

$$Z_{InflowFB^{Comp}_{ct}} = \frac{\sum_j [\lambda_j^{c,t=0} (\sum_i I_{im} * NewImm_{ijt})]}{\sum_i ColEdu_{ic,t-5}}.$$

Everything is as previously described, except that the new immigrant from country j dummy variable ($NewImm_{ijt}$) is interacted with I_{im}, an indicator if individual i has a competing major for a native with major m. Thus, the instrument for inflows of competing immigrants, like the inflow variable, varies at the major-by-MSA level. The instrument for inflows of noncompeting immigrants is defined analogously with $Z_{InflowFB^{NComp}_{cmt}} = Z_{InflowFB_{ct}} - Z_{InflowFB^{Comp}_{cmt}}$.

In most shift-share research designs, exogeneity of the instrument can come from either exogeneity of either the shift component (Borusyak et al., 2022) or exogeneity of the share component (Goldsmith-Pinkham et al., 2020). While this holds for our instrument for the overall inflow rate of college-educated immigrants ($Z_{InflowFB_{ct}}$), exogeneity of our instruments for competing and non-competing immigrants necessarily come from the shift component of the instrument as this is the only component of the instrument that varies at the major-by-MSA level. Therefore, identification relies on their being meaningful shocks in the composition of national arrivals by major over time. These shocks are also important to address the critique of shift-share instruments in Jaeger et al. (2018), who raise concerns that inflows of immigrants may be correlated over time and thus, the dynamic adjustment process of past waves of immigration could bias shift-share IV models.

As we show in Figure 3 and Appendix Table A3, there are indeed meaningful shocks in the composition of national arrivals over time – both at the country-level and the country-by-major level. Figure 3 shows that college-educated immigration has steadily increased over the 2012-2019 period from Central/South American and China and decreased from the UK, Western Europe, the Philippines, and other Asian countries. Appendix Table A3 presents these trends at the major-by-country level. Therein, we depict a similar pattern of relative growth and contraction across countries. However, Appendix Table A3 also shows that there is also variation across majors within a country. For example, while the proportion of college-educated immigrants from Central/South America increased by three percentage points overall, the growth in business and education majors was much larger (4.0 and 4.7 percentage points, respectively) than the increase in computer science majors (1.3 percentage points).

To further aid identification, we also adjust Equation 1 and 2 and include lagged city-specific demographic variables ($X_{c,t-5}$) in the specification including: a quadratic in average age and the share of the population that is Black (where all values represent averages from five years prior for the college-educated sample). These demographic controls could be important as they could be correlated with both changes in labor market outcomes and the local demand conditions that attract immigrants to MSAs. That said, we also present robustness estimates that exclude these lagged MSA-level demographics.

4.3 Extensions

We extend Equation 1 and 2 in a few ways to test the sensitivity of our results to alternative identifying assumptions and explore the value added of our approach. First, our immigrant inflow variables have (thus far) been limited to college graduates. However, less-educated workers may also impact the labor market outcomes of college-educated natives and these inflows of less-educated immigrants may be correlated with the inflows of college-educated immigrants, biasing our estimates when they are excluded. Thus, accounting for inflows of less-educated immigrants may be important. To address this, we extend Equation 2 and include a third inflow of immigrants, non-college educated immigrants. Thus, in this expression, natives with a given major face inflows of competing college-educated immigrants, non-competing college-educated immigrants, and non-college educated immigrants.

Second, we have argued that college major is a better way to determine who competes with whom (than occupational employment) and thus, a better way to evaluate the impact of inflows of competing and non-competing immigrants. However, this remains an empirical question as college major could miss other important dimensions of skills. Thus, we reestimate our main empirical expressions using occupational employment to determine who competes with whom, where immigrants employed in the same broad occupational grouping constitute competing immigrants and immigrants in a different broad occupational group constitute non-competing immigrants. We then compare these estimates with estimates where we use college major to determine who competes with whom. This extension helps assess the extent to which college major offers additional insights above and beyond using occupational employment.

Third, we explore heterogeneity in outcomes, including by worker demographic characteristics and by industry. Many studies have found that new immigrants compete more directly with younger workers and are more complementary with older workers (Borjas, 2003). Thus, we examine how our estimates of the impact of competing and non-competing immigrants intersect with these age-based (and other demographic-based) subsamples of natives. We then analyze heterogeneity by industry to better understand the underlying causes of the non-competing effects we estimate; specifically, whether our estimates are likely to be due to production complementarities or increased demand for non-tradable service goods. These different explanations imply a different industrial allocation of the estimated non-competing effects, with production complementarities most evident in those industries where most new immigrants are employed but effects stemming from increased demand for service goods should, naturally, be most evident in the service sector. Thus, we explore how our estimated non-competing effects vary across these industrial groups.

5 Results

5.1 First Stage Regression Results

Table 3 presents the first-stage regression results using different instruments, where the instruments differ by the sample and data source used to construct the pre-existing settlement pattern of earlier arriving immigrants (λ). The first two columns use the sample of aged

25-60 immigrants from the 2000 Decennial Census and the second two columns use the sample of aged 25-60 immigrant from the 1990 Decennial Census. The first column under each data source, i.e. column (a) and (c), limit the sample of immigrants to college-educated immigrants while the second column under each data source, column (b) and (d), use all aged 25-60 immigrants in the respective data source.

The strength of the instruments decreases as we move from (a) to (d) – with pre-existing settlement pattern shares associated with more recent immigrants and more-similarly skilled immigrants stronger predictors of the geographic allocation of new immigrants in the 2017-2019 ACS. That said, a stronger instrument does not necessarily imply that it is a better instrument – especially if there are concerns that the instrument is correlated with the same unobserved changes in demand conditions as the inflow shares. At the same time, however, the instruments using the 1990 Decennial Census are clearly weak (Andrews et al., 2019). Thus, while our preferred instruments use the settlement patterns of college-educated immigrants from the 2000 Decennial Census, we present estimates using all four sets of instruments to test the sensitivity of our results to the sample used to construct λ.

5.2 Main OLS and IV Results

Table 4 presents our empirical results (OLS and IV) documenting how inflows of college-educated immigrants affect the geographic allocation and employment outcomes of native college graduates. Panel 1 presents the effects on the total number of college graduates in an MSA. These results help assess whether inflows of immigrants are inducing outmigration of native college graduates (and biasing our estimates). The results show that immigrant inflows are not causing a net change in the number of native college graduates in an MSA. While the OLS estimates imply that immigrant college graduates are moving to areas that are also attracting an increasing number of native college graduates, our IV strategy corrects for this strategic sorting. College-educated immigrant inflows do not change the overall number of native college graduates, with no evidence that inflows of competing immigrants push away similarly skilled immigrants and no evidence that inflows of non-competing immigrants pull in differently skilled immigrants. Thus, we find no evidence of outmigration, validating our MSA-by-MSA empirical approach.

Panel 2 and 3 of Table 4 present the effects of immigrant inflows on the probability of native employment (Panel 2) and full-time employment (Panel 3). The IV estimates imply that college-educated immigrants have increased the probability that natives are employed but have had no overall effect on full-time employment probabilities. The 0.16 (0.05) coefficient on overall employment implies that a 10 percent increase in the college-educated immigrant share, increases native college-educated employment by 1.6 percentage points. Despite this average effect, the estimates on inflows of competing and non-competing immigrants imply that increases in overall employment are largely driven by inflows of non-competing immigrants with no effect from inflows of competing immigrants. The estimates imply that inflows of, for example, immigrant STEM majors are not impacting the employment opportunities of native STEM majors but increasing opportunities for non-STEM college graduates. Thus, majors with the largest inflows of non-competing immigrants have experienced the largest increases in employment.

The heterogeneous impact of immigrant inflows on native labor market outcomes is even more evident when we examine the impact of immigration on full-time employment. Inflows of non-competing immigrants again increase full-time employment probabilities with an estimated elasticity of 0.27 (0.13). However, we also see that inflows of competing immigrants actually decrease full-time employment opportunities for natives with a sizable negative coefficient of -0.75 (0.37). While these effects largely cancel each other out for the average college-educated native (who faces a non-competing inflow rate of 3.8 percent and a competing inflow rates of 0.9 percent), the estimates imply variation in outcomes across college majors. For example, the average education major (in the 40 largest MSAs) experiences non-competing immigrant inflows of 4.7 percent and competing immigrant inflows of 0.2 percent, amounting to predicted increase in full-time employment of 1.1 percent. That said, the average computer science major experiences non-competing inflows of 2.9 percent and competing inflows of 1.8 percent, which amounts to a predicted 0.6 percent decline in full-time employment.

The estimated employment effects from inflows of competing and non-competing immigrants also imply heterogeneity that varies at the MSA-by-major level. This variation and comparisons to the predicted effects implied by Equation 1 are depicted in Figure 4. The histogram on the left side of the figure plots the distribution of the two sets of predicted effects of immigrant inflows on native full-time employment: $\Delta\hat{Y}_c = \hat{\beta}_1\overline{InflowFB_c}$

from Equation 1 versus $\Delta\hat{Y}_{cm} = \hat{\beta}_2 \overline{InflowFB^{Comp}_{cm}} + \hat{\beta}_3 \overline{InflowFB^{NComp}_{cm}}$ from Equation 2.[25] Across all MSAs, the predicted effects on full-time employment (associated with immigrant inflows over the previous five years) were largely positive, but generally small. That said, the histograms demonstrate that the variation in predicted outcomes on full-time employment is larger when one accounts for inflows of competing and non-competing immigrants, i.e. the spread of the histogram is wider in the MSA-by-major predicted effects from Equation 2 ($\Delta\hat{Y}_{cm}$) than the MSA-level predicted effects from Equation 1 ($\Delta\hat{Y}_c$). The scatter plot on the right side of Figure 4 presents the variation across majors within MSAs for the 15 largest MSAs – with the predicted MSA-level effect from Equation 1 on the x-axis, the predicted MSA-by-major effects from Equation 2 on the y-axis, and bubble sizes are proportional to the size of the native sample. The scatter again demonstrates that there is additional variation in predicted outcomes when one accounts for inflows of competing and non-competing immigrants – with substantial variation across majors (within a MSA). The figure also shows that both the average effect and the variation across majors increases as the overall inflow rate of immigrants increases. Thus, MSAs with the largest immigrant inflows tended to experience larger increases in full-time employment, but the variation across majors within the MSA also increased.

Table 5 presents the estimated effects of immigrant inflows on the earnings of native college graduates. The IV estimates of Equation 1 imply that inflows of college-educated immigrants over our period of analysis have had no measurable effects on overall earnings, even though all of the coefficients are positive. This is true regardless of the native sample analyzed: including all natives even the non-employed (Panel 1), limiting the sample to employed natives (Panel 2), or limiting the sample to full-time employed natives (Panel 3). That said, the IV estimates of Equation 2, which are presented in column (d) of Table 5, imply that there is heterogeneity in outcomes across the native sample – with strong evidence that inflows of competing immigrants decrease earnings, but inflows of non-competing immigrants increase earnings. The estimated elasticity associated with inflows of competing immigrants is -1.04 when we include part-time workers in the sample and -0.60 when we limit the sample to full-time workers. This difference in the estimates implies that some

[25] $\overline{InflowFB_c}$ is the average five-year inflow of immigrants into MSA c in the 2017-2019 ACS; and $\overline{InflowSh^{Comp}_{cm}}$ ($\overline{InflowSh^{NComp}_{cm}}$) is the average five-year inflow of competing (non-competing) immigrants into MSA c for major m in the 2017-2019 ACS.

of the overall earnings losses (on all employed natives) come from competing immigrants' impact on full-time employment, decreasing full-time work and increasing part-time work.[26] However, the negative effects of competing immigrants on earnings of full-time workers in Panel 3 implies that there is also a wage effect – with inflows of competing immigrants lowering native wages. The estimated elasticity on inflows of non-competing immigrants is about 0.7 when non-employed workers are included and about 0.5 when non-employed workers are excluded (regardless of whether part-time workers are included or not in the sample). The different coefficients capture the effects of non-competing immigrants on overall employment. That said, inflows of non-competing immigrants also increase native wages, which is evidenced by their impact on full-time earnings.[27]

The net effect of these countervailing impacts on earnings is positive for the average native worker but again varies by major and at the major-by-MSA level.[28] This variation in the predicted effects of immigrant inflows on earnings is depicted in Figure 5, which shows the predicted effects of college-educated immigrants on native earnings for all employed workers. Interestingly, the variation in predicted outcomes, shown in the histogram, is fairly similar regardless of whether we use the total inflow of college-educated immigrants or the inflows of competing and non-competing immigrants. That said, the scatter plot shows that there is still a lot of variation across majors within MSAs. For example, the average education and health major in Miami experienced predicted earnings gains of about 4 percent while native business majors in Miami experienced earnings losses of about 1 percent. While these predicted effects are almost largely positive, the one group of natives that tends to experience small earnings losses are native computer science majors. The results are very similar if we examine the predicted impact on full-time earnings (see Appendix Figure A1), although the negative effect on computer science majors becomes less evident. This implies that the earnings losses of computer science majors in Figure 5 largely come through the full-time/part-time margin – decreasing full-time work and increasing part-time work.

[26]The fact that the estimated coefficients on earnings are essentially unchanged whether we include non-workers or not (see Panel 1 and Panel 2 estimates of the impact of competing immigrants) is consistent with the employment results where we see no impact of competing immigrants on employment.

[27]The increase in full-time employment due to non-competing immigrants does not appear to lower the positive effect on earnings (i.e. the coefficients are unchanged between Panel 2 and 3).

[28]The average native college-graduate experienced an inflow of competing immigrants of about 4 percent and an inflow of non-competing immigrants of about 1 percent, again implying an average impact of about 1.5 percent.

It is also instructive to compare the OLS and IV estimates in Table 4 and Table 5 to explore bias in the OLS estimates. As expected, the OLS estimates of inflows of competing immigrants tend to understate the negative impacts of competing immigrants. This likely reflects that immigrants positively select to geographic areas with elevated labor demand for their skills. For natives, this means that large inflows of immigrants with similar skills (i.e. competing immigrants) will tend to be associated with elevated labor demand for these workers. However, it is not obvious what large inflows of non-competing immigrants (i.e. immigrants with different skills) means about demand conditions for one's skills/major. If the demand shock attracting the non-competing immigrants is major specific, it might imply weak labor demand conditions for these natives, but if the demand shock is broader, it could imply strong labor demand conditions for these natives. Thus, it is not obvious what the natural bias is from OLS estimates when natives experience large inflows of non-competing immigrants. The estimates in Table 4 and 5, however, show that the OLS estimates on inflows of non-competing immigrants tend to understate the positive effects of inflows of non-competing immigrants. Therefore, inflows of non-competing immigrants tend to be negatively selected (from the point of view of natives) – i.e., the labor demand shocks that attract immigrants to geographic areas tend to be skill-specific. Moreover, since non-competing immigrants tend to make up a larger proportion of college-educated immigrants than competing immigrants, the negative selection of non-competing immigrants dominates the positive selection associated with competing immigrants, meaning that the OLS estimates of the total inflows of college-educated immigrants from Equation 1 tend to understate the postive effect in the IV estimates.

5.3 Robustness of IV Estimates

We next explore the sensitivity of our results to using different instruments as well as small specification changes to our main empirical expression. Table 6 presents the IV estimates using the four different instruments, where the instruments differ in the sample of immigrants and the data source used to compute the pre-existing settlement pattern of earlier arriving immigrants. The results are striking in terms of the pattern of estimates as the samples used to compute the push shares (i.e. λ's) become increasingly different from the inflow sample – both in terms the education restrictions associated with the immigrant sample in the Decennial Census and the timing of immigrant arrival associated with the different data sources. Specifically, as the sample used to construct the λ's become more-and-more distinct from the inflow sample, the IV estimates become increasingly different from the OLS estimates and continue to suggest that the OLS estimates both understate the negative effects of competing immigrants and understate the positive effects of non-competing immigrants. At the same time, however, the precision of the estimates decreases as we move from our main IV estimates reproduced in column (b) to the alternative estimates in column (c)-(e), making the estimates statistically indistinguishable from each other. Thus, all of estimates in Table 6 imply the same basic pattern of results with natives experiencing heterogenous effects that depend upon the composition of immigrants and the extent to which they are competing or non-competing.

Table 7 presents additional robustness estimates of our empirical specification. The results are largely unchanged if we measure inflows of immigrants using the change in the total number of immigrants from five years prior (see column b) as opposed to using the year of arrival variable in the ACS; if we exclude the demographic controls from the empirical analysis (column c); if we add back in native double majors (column d); if we make small adjustments to the IOC-based definition of a competing immigrant (columns e and f); or if we disaggregate the business and liberal arts majors into smaller groups (column g). That said, in most of these instances, the precision of the estimates decreases. Table 7 also shows that the results are robust to the inclusion of less-educated natives – with inflows of competing immigrants continuing to impose costs on native college graduates and inflows of non-competing immigrants continuing to bestow benefits (see column h). While the magnitude of the coefficient estimates (when we include less-educated immigrants) are substantially larger than when they are excluded from the specification, this is entirely because the inflow shares of competing/non-competing immigrants have decreased as the same number of competing/non-competing immigrant inflows is now divided by a much larger denominator, which now also includes non-college educated workers. Thus, our exclusion of less-skilled immigrants from our primary analysis does not affect the basic conclusions of the analysis. Interestingly, these estimates also imply that non-college educated immigrants do not affect the labor market outcomes of college-educated natives.

One notable difference between our baseline estimates and the robustness estimates is that the negative impact of competing immigrants on full-time earnings becomes less evident. While the coefficient remains negative in all of the alternative specifications, it is no longer statistically significant in five of the seven extensions. Thus, the negative impact of competing immigrants on the wages for full-time employed native college graduates is less robust than the other results.

5.4 College Major vs. Occupations

The question remains: does college major do a better job of highlighting the competing and non-competing effects of college-educated immigration than occupational employment? To assess this question, we reestimate our empirical expressions where we redefine a competing and non-competing immigrant in terms of the similarity of occupational employment, with competing (non-competing) immigrants working in the same (different) broad occupation category.[29] Estimates that use occupational employment to define competing/non-competing immigrants will weaken the positive effects of college major based definitions of non-competing immigrants, biasing them towards zero, if natives compete with immigrants outside of their occupation or if natives are negatively affected by similarly skilled but underemployed immigrants. Occupation-based estimates will also weaken the negative effects of competing immigrants (using the college major based definition) if immigrants push natives out of their preferred job or natives do not compete with all immigrants within their occupation. That said, the occupation-based estimates of competing/non-competing immigrants may be similar to the college major-based estimates simply because college major and occupational employment are highly correlated (see Figure 1 and 2).

To further disentangle the impact of occupations separate from college major, we also re-estimate the occupation-based estimates after we split the immigrant sample in terms of whether they are employed in occupations that "match" their college major or not, where an occupation/major "match" is defined as the college major with the largest number of people employed in a given occupation. So, e.g., business majors are matches for business and

[29]The broad occupation categories we use include business occupations (including sales), managers, computer occupations, engineering occupations, science occupations, health care occupations, professional service occupations, production occupations (including construction, repair workers, protective service workers, and agriculture), and other service occupations (largely low-skill service).

managerial occupations.[30] Under this set-up, an occupation-based competing immigrant in the "matched" sample is now also a college-major based competing immigrant and the same is true for non-competing immigrants -– with all non-competing immigrants in the matched sample representing both occupation and college-major based non-competing immigrants. On the other hand, in the unmatched sample, an occupation-based competing immigrant now largely reflects immigrants working in the same occupation but not having the same college major.[31] Non-competing immigrants in the unmatched sample are also less-likely to reflect a college-major based non-competing immigrant. Thus, if college major matters more than occupation, then we would expect to see more similar estimates in the occupation-based estimates when we limit the sample of immigrants to "matched" immigrants. On the other hand, if occupation matters over-and-above college major, then we should estimate similar effects using the unmatched sample. Thus, estimates using these two subsamples help us disentangle the impact of occupation over-and-above college major.

The IV estimates using occupation-based definitions of competing/non-competing are presented in columns (a)-(c) of Table 8. The full sample estimates in column (a) show that when we use occupation to define competing and non-competing immigrants we find that there are no material effects on native college graduates associated with inflows of college-educated immigrants. Interestingly, we do not even see the same basic pattern of estimates (as the college major-based estimates) with negative coefficients on inflows of competing immigrants and positive coefficients on inflows of non-competing immigrants. When we split the sample, however, and estimate the impacts of inflows of "matched" occupation-based competing and non-competing immigrants, the estimated effects are now much closer to (although noisier than) the college-major based estimates of competing and non-competing immigrants. Thus, when we make the occupation-based measures of competing and non-competing immigrants more closely aligned with college-major based definition of competing and non-competing immigrants, the estimates start to look more similar. That said, we find

[30]Occupational matches for computer science/math majors are computer occupations, for engineering majors are engineering jobs, for science majors are science occupations, for education majors are education occupations; for health majors are health occupations; and for liberal arts majors are professional service jobs, other service jobs, and production jobs.

[31]The only exceptions here are those majors with more than one competing immigrant major, i.e. native computer science majors and native science majors. In these instances, we assign the immigrant major with the most employed people in the occupation. So, while computer science and math is the matched major to the computer occupation, competing immigrants for computer occupations are the largest of immigrant sample working in these jobs: immigrant computer science majors or immigrant engineering majors.

no evidence that inflows of "unmatched" occupation-based competing and non-competing immigrants affect native labor market outcomes. Thus, the occupation-based results suggest that occupations alone offer little insight into who competes with whom over-and-above college major.

We further explore the superiority of using college major to define competing/non-competing immigrants vis-à-vis occupational employment in columns (d) and (e) where we present estimates using our college major-based definition of competing/non-competing immigrants, but where we again split the immigrant sample by whether they are employed in occupations that match/don't match their college major. While the magnitudes of the coefficients differ between the two sets of estimates,[32] we find the same basic pattern of estimates – with competing immigrants imposing costs and non-competing immigrants bestowing benefits – regardless of whether these competing/non-competing immigrants are employed in occupations that match or don't match their college major. Thus, the estimates imply that, for example, inflows of immigrant computer science majors impose similar costs on native computer science majors and bestow similar benefits on other native college graduates, regardless of whether they are employed in a computer science job or not. Therefore, the main takeaway of these results is similar to the takeaway from the matched/unmatched occupation-based estimates – college major appears to be a better way to capture who competes with whom than occupational employment.

5.5 Demographic and Industrial Heterogeneity

Lastly, we explore heterogeneity in our results by demographic groups and across industries. These results help us assess the distributional consequences of college-educated immigrant inflows and analyze the underlying cause of the large non-competing effects we estimate. Demographically, we explore variation by age and sex because there is a long history of examining heterogeneity of immigrant inflows by worker age (Borjas, 2003) and differences in occupational employment by sex (Blau et al., 2013) could weaken our college-major based definitions of competing and non-competing immigrants. Next, we explore heterogeneity by industry to better understand whether the non-competing effects we estimate are due to production complementarities or growth of the service sector. If the non-competing effects

[32]The difference in coefficient magnitudes likely reflects changes in the magnitudes of the inflow variables as opposed to larger or smaller effects on the outcome.

represent production complementarities, then the estimated non-competing effects should be most evident in those sectors where most college-educated immigrants are employed. On the other hand, if the non-competing effects reflect increased demand for local services, then the non-competing effects should be most evident in the local service sector.

Table 9 presents the estimates of Equation 1 and 2 on the different demographic subsamples from the ACS. Columns (a)-(b) show the IV estimates when the sample is split by age: younger natives aged 25-40 vs. older natives aged 41-60. We find that competing immigrants impose larger costs on younger college-educated natives with estimated effects that are at least three times larger than the estimated effects on older college-educated natives, with none of the effects on older college-educated natives being statistically different than zero. This result is consistent with earlier findings that new immigrants more directly compete with younger natives. However, we find less evidence that older workers are more complementary to new immigrants. Rather, the coefficients on inflows of non-competing immigrants show that younger workers experience more-positive impacts from inflows of non-competing immigrants on employment and similarly size effects of earnings. Therefore, younger natives appear to be both more substitutable and more complementary to new immigrants than older natives.

The estimates by sex in columns (c) and (d) are harder to interpret but seem to suggest that both men and women are affected by inflows of college-educated immigrants. That said, the estimated effects on men are most evident on men's employment while the estimated effects on women are most evident on their earnings – suggesting, somewhat surprisingly, that college-educated women's labor supply appears to be more inelastic than college-educated men's labor supply.

Table 10 presents IV estimates where we split the ACS sample by industry: (i) immigrant intensive industries vs. non-intensive industries and then (ii) non-tradable service sector vs. all other industries.[33] As shown in column (a) and (b), competing immigrants impose similar costs in immigrant intensive and non-intensive industries, but the non-competing effects of immigrant inflows are almost entirely felt in immigrant intensive industries. Moreover, the estimated non-competing effects in immigrant intensive industries are all statistically sig-

[33] We define an immigrant intensive industry as the industries where the highest proportion of immigrants are employed. These include: the professional service sector, the information sector, the healthcare sector, and the finance sector. The non-tradable service sector includes education, utilities, construction, and government.

nificant at the one percent level while only the impact on overall employment is statistically significant in non-intensive industries. Looking at the local service sector (excluding the immigrant intensive sectors), we again see vastly different estimates of the non-competing effects, but now all of the effect is evident in industries other than the local service sector. Moreover, these results are robust to including the retail and low-skill service sector in the local service sector group or moving healthcare out of the competing industries and into the local service sector.

Taken together, the large non-competing effects in immigrant intensive industries, which include professional services, information, healthcare, and real estate, combined with no comparable non-competing effects in other local service sectors suggest that the positive non-competing effects that we estimate occur in those industries where immigrants are most likely to be employed but not in other local service industries. Thus, production complementarities that increase the demand for differently skilled natives appear to explain the non-competing effects we estimate.[34] That said, these immigrant intensive industries are also service industries. Therefore, we cannot fully rule out that increased local demand for local services also explains some portion of the elevated non-competing effects in these industries.

6 Conclusion

This paper uses the college majors of natives and immigrants to separately define inflows of competing and non-competing college-educated immigrants. We then use geographic variation in the inflows of college-educated immigrants with different college majors to assess the heterogenous effects of high-skill immigration on the labor market outcomes of college-educated native workers in the U.S.

We find that inflows of college-educated immigrants over the 2012-2019 period led to small increases in overall employment but no overall change in average earnings. However, these average effects mask a great deal of heterogeneity across college majors and metropolitan areas as the size and composition of these immigrant inflows (competing vs.

[34] Interestingly, younger natives are more likely to be employed in these immigrant intensive industries than older workers. Thus, some portion of the larger non-competing effects for younger workers may simply be that they experience larger increases in demand (via production complementarities) because of their industrial allocation.

non-competing) vary at the major-by-MSA level. Indeed, we show that inflows of competing immigrants have detrimental effects on native college graduates, lowering full-time employment and earnings. On the other hand, inflows of non-competing immigrants increase overall employment, full-time employment, and earnings. Thus, like the effects of international trade (Autor et al., 2016), we find that high-skill immigration can produce winners and losers (Price et al., 2020), even if the U.S. labor market has benefitted on net. However, over our period of analysis, we find that a vast majority of college-educated natives benefitted from inflows of college-educated immigrants because all natives were exposed to inflows of both competing and non-competing immigrants and college-educated immigrants were largely non-competing for native college graduates.

Our results are unique to using college major to define competing and non-competing immigrants – with occupation-based measures producing more muted and noisy competing and non-competing effects. Thus, skills appear to be broader than occupation-specific. Moreover, the fixed nature of college major helps solve the endogeneity of occupational employment. We also show that the large non-competing effects that we estimate are most evident in those sectors that employ the most immigrants, i.e. the professional service, information, healthcare, and finance sectors. At the same time, we see no measurable spillover in other locally produced service sectors. This combination of results suggests that the non-competing effects appear to be due to production complementarities (that increase the demand for differently skilled natives) and not increased demand for local services.

This analysis makes several important contributions to the immigration literature. First, our results unify the seemingly disparate findings that sometimes suggest that college-educated immigrants harm native labor market outcomes (Borjas, 2005; Borjas and Doran, 2012) while at other times appear to benefit native labor market outcomes (Peri et al., 2015) or have no effect (Kerr, 2013). We show that all of the above results are possible and depend importantly on the skill mix between natives and immigrants and the specific sample being analyzed. Second, we show that immigrants can have sizeable positive effects on native labor market outcomes if the skills differ sufficiently from the native population. This is a point that has been made numerous times (see e.g. Altoni and Card, 1991) but has generally been difficult to show empirically. Third, our analysis highlights the importance of estimating the overall effects of immigrant inflows (Dustmann et al., 2016) as opposed to estimating the relative effects. While other studies have shown that inflows of immigrants with the same college major harm the relative labor market outcome of natives with the same major (Turner, 2022), our results show that this relative decline is largely driven by gains for workers with different majors and not losses by workers with the same major. The policy implications of this difference are stark and suggest that caution is warranted when evaluating studies that estimate relative effects. Lastly, our analysis highlights the usefulness of using college major to help determine who competes with whom in the labor market.

In conclusion, our analysis shows that it is not the quantity of college-educated immigrants that affects native labor market outcomes, but rather the skill mix of immigrants and how they match the skills of the local native population. Therefore, to both minimize the labor market costs and maximize the labor market gains from high-skill immigration, immigration policy should not just consider the desired skills of immigrants but also the composition of natives in the specific geographic areas where new immigrants are likely to reside.[35] Indeed, if this is done properly, our results show that college-educated immigration can bestow sizeable benefits on a large share of the native population without substantially impacting the labor market outcomes of those workers that face more direct competition from immigrants.

[35]Of course, policymakers should also consider other aspects of immigration beyond the labor market impacts including immigrants' effect in innovation (Hunt and Gauthier-Loiselle, 2010) and immigrants' impact on other non-economic factors (Dustmann and Preston, 2019).

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Table 1: Summary Statistics on College-Educated Sample in 2017-2019 American Community Survey

	Domestic Born				**Foreign Born**			
	Full Sample	**Under Age 40**	**Men Only**	**Women Only**	**Full Sample**	**Arrived Before Age 20**	**Arrived Age 20+**	**Arrived Last 5 Years, Age 20+**
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Age	41.6	32.0	41.9	41.4	42.1	40.1	43.0	36.2
Female	0.53	0.54	0.00	1.00	0.52	0.53	0.52	0.51
Black	0.11	0.11	0.09	0.12	0.09	0.11	0.08	0.07
Asian	0.05	0.08	0.05	0.05	0.50	0.46	0.51	0.51
White	0.82	0.78	0.83	0.80	0.36	0.36	0.36	0.37
Hispanic	0.08	0.10	0.08	0.08	0.18	0.22	0.17	0.18
College Major								
Business	0.26	0.24	0.30	0.22	0.25	0.28	0.24	0.24
Engineering	0.08	0.07	0.14	0.03	0.19	0.12	0.21	0.23
Computer Science	0.05	0.05	0.07	0.03	0.10	0.08	0.11	0.13
Science	0.08	0.08	0.08	0.08	0.10	0.11	0.10	0.08
Health	0.06	0.07	0.02	0.10	0.08	0.08	0.08	0.05
Education	0.08	0.07	0.04	0.12	0.05	0.04	0.05	0.05
Liberal Arts	0.39	0.42	0.35	0.43	0.23	0.28	0.21	0.21
Graduate Degree	0.36	0.32	0.33	0.38	0.43	0.37	0.46	0.45
Employed	0.88	0.92	0.92	0.85	0.82	0.88	0.80	0.74
Employed Full-time (FT)	0.74	0.77	0.81	0.67	0.68	0.74	0.65	0.55
Earnings of FT Workers	103.1	81.7	121.6	83.6	104.7	102.8	105.6	91.3
Weekly Hours of FT Workers	44.6	44.0	45.9	43.2	43.4	43.7	43.2	43.1
N	703,808	304,458	325,724	378,084	200,215	59,660	140,555	36,585

Notes: The analysis uses the 2012-2019 American Community Survey data on individuals aged 25-60 with a college degree from the 40 largest metropolitan areas in the United States. Since the outcomes in our empirical analysis are five-year changes in average employment outcomes, the main sample uses observations from 2017-2019. Business majors include accounting, finance, economics, marketing, management, and general business majors. Computer science majors include math majors. Liberal arts majors largely include the humanities, the social sciences (other than economics), the fine arts, and communications. See Appendix Table A1 for a complete list of the unique college majors included in each aggregated college major listed above.

Table 2: Index of Congruence of Occupational Employment

	Foreign-Born College Majors						
Native-Born College Majors	**Business**	**Engi- neering**	**Computer Science**	**Science**	**Health**	**Education**	**Liberal Arts**
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
Business	0.73	-0.24	-0.15	-0.31	-0.35	-0.27	-0.18
Engineering	-0.19	0.75	0.13	-0.03	-0.18	-0.21	-0.28
Computer Science	-0.04	0.55	0.91	-0.01	-0.19	-0.17	-0.20
Science	-0.26	-0.08	-0.11	0.82	0.22	-0.09	-0.08
Health	-0.24	-0.22	-0.16	0.05	0.90	-0.07	-0.17
Education	-0.27	-0.26	-0.18	-0.15	-0.12	0.67	-0.07
Liberal Arts	-0.21	-0.47	-0.34	-0.29	-0.31	0.01	0.53

Notes: The index of congruence is a statistic describing the similarity of occupational employment between native-born and foreign-born college graduates by major. Like a correlation coefficient, an index of congruence value sits on the [-1,1] interval, where a value of -1 implies perfect occupational segregation and a value of 1 implies perfect occupational overlap. Business majors include accounting, finance, economics, marketing, management, and general business majors. Computer science majors include math majors. Liberal arts majors largely include the humanities, the social sciences (other than economics), the fine arts, and communications. See Appendix Table A1 for a complete list of the unique college majors included in each aggregated college major listed above.

Table 3: First-Stage Regression Results by Sample used to Construct Instrument

	Sample Used to Construct Pre-existing Settlement Pattern Shares			
	2000 Census		1990 Census	
	College-Educated Immigrants	All Immigrants	College-Educated Immigrants	All Immigrants
	(a)	(b)	(c)	(d)
Panel 1: Inflows of All Immigrants				
Instrument for All Immigrants	0.81***	0.79***	0.63***	0.55***
	(0.13)	(0.20)	(0.23)	(0.22)
R^2	0.57	0.49	0.33	0.27
F-Statistic	37.9	15.6	7.7	6.4
Panel 2: Inflows of Competing Immigrants				
Instrument for Competing Immigrants	1.30***	1.26**	0.96*	0.80*
	(0.30)	(0.47)	(0.50)	(0.47)
Instrument for Noncompeting Immigrants	-0.11***	-0.10*	-0.07	-0.06
	(0.04)	(0.06)	(0.06)	(0.06)
R^2	0.67	0.60	0.48	0.44
F-Statistic	16.4	8.6	4.7	3.8
Panel 3: Inflows of Noncompeting Immigrants				
Instrument for Competing Immigrants	-0.47**	-0.40	-0.34	-0.21
	(0.19)	(0.28)	(0.29)	(0.26)
Instrument for Noncompeting Immigrants	0.91***	0.88***	0.71**	0.60**
	(0.16)	(0.25)	(0.28)	(0.26)
R^2	0.59	0.51	0.35	0.30
F-Statistic	23.9	13.3	6.1	5.4

Notes: This table presents estimates of the first stage IV regression, regressing inflow rates of different immigrants groups on their respective instrument and other covariates including major-by-year fixed effects and demographic controls for the share black and a quadratic in average implied experience. The instruments differ by the sample used to construct the pre-existing settlement pattern of earlier arriving immigrants from a given home country. Columns (1)-(2) use the 2000 Decennial Census. Columns (3) and (4) use the 1990 Decennial Census. All observations are aggregated to the msa-by-major year level with N=840 for all specifications. All standard errors are clustered at the MSA-level. * p<0.1; ** p<0.05; and *** p<0.01

Table 4: Employment Effects of Inflows of College-Educated Immigrants

	All College-Educated Immigrants		Competing/ Noncompeting College-Edu Immigrants	
	OLS	**IV**	**OLS**	**IV**
	(a)	(b)	(c)	(d)
Panel 1: Total Number of College Graduates				
Inflow Rate of All College-Educated Immigrants	0.72**	0.16		
	(0.33)	(0.33)		
Inflows of Competing Immigrants			0.65*	-0.57
			(0.37)	(0.83)
Inflows of Non-Competing Immigrants			0.74*	0.33
			(0.39)	(0.38)
Panel 2: Employment Probabilities				
Inflow Rate of All College-Educated Immigrants	0.08*	0.16***		
	(0.04)	(0.05)		
Inflows of Competing Immigrants			-0.06	0.07
			(0.16)	(0.22)
Inflows of Non-Competing Immigrants			0.11**	0.18*
			(0.05)	(0.10)
Panel 3: Full-Time Employment Probabilities				
Inflow Rate of All College-Educated Immigrants	0.02	0.07		
	(0.07)	(0.08)		
Inflows of Competing Immigrants			-0.64**	-0.75**
			(0.24)	(0.37)
Inflows of Non-Competing Immigrants			0.17**	0.27**
			(0.08)	(0.13)
First Stage F-Statistic for Instruments				
All College-Educated Immigrants		37.9		
Competing Immigrants				16.4
Non-Competing Immigrants				23.9

Notes: All estimates use changes in major-by-MSA totals over the five-year periods 2012-2017, 2013-2018, and 2014-2019. With 40 MSAs, seven majors, and three years (of five-year changes), all regressions have 840 observations. “Competing” immigrants for a native college major are all immigrants with a college major that has an IOC value greater than 0.2. “Non-competing”immigrants are all other immigrants. Full-time employed workers are defined to be individuals working at least 48 weeks in the past year, averaging at least 30 hours, and being paid a wage at least as large as the minimum wage. All standard errors are clustered at the MSA-level. * p<0.1; ** p<0.05; and *** p<0.01

Table 5: Earnings Effects of Inflows of College-Educated Immigrants

	All College-Educated Immigrants		Competing/ Noncompeting College-Edu Immigrants	
	OLS	**IV**	**OLS**	**IV**
	(a)	(b)	(c)	(d)
Panel 1: All College Graduates (Includes Non-Employed)				
Inflows of All College-Educated Immigrants	0.28*	0.37		
	(0.16)	(0.26)		
Inflows of Competing Immigrants			-0.90**	-0.94**
			(0.39)	(0.38)
Inflows of Non-Competing Immigrants			0.56***	0.68**
			(0.19)	(0.33)
Panel 2: All Employed College Graduates				
Inflows of All College-Educated Immigrants	0.18	0.17		
	(0.15)	(0.22)		
Inflows of Competing Immigrants			-0.83**	-1.04***
			(0.35)	(0.35)
Inflows of Non-Competing Immigrants			0.41**	0.45*
			(0.18)	(0.24)
Panel 3: All Full-Time Employed College Graduates				
Inflows of All College-Educated Immigrants	0.26*	0.28		
	(0.15)	(0.21)		
Inflows of Competing Immigrants			-0.35	-0.60**
			(0.25)	(0.29)
Inflows of Non-Competing Immigrants			0.41**	0.49**
			(0.18)	(0.24)
First Stage F-Statistic				
All College-Educated Immigrants		37.9		
Competing Immigrants				16.4
Non-Competing Immigrants				23.9

Notes: All estimates use changes in major-by-MSA totals over the five-year periods 2012-2017, 2013-2018, and 2014-2019. With 40 MSAs, seven majors, and three years (of five-year changes), all regressions have 840 observations. "Competing" immigrants for a native college major are all immigrants with a college major that has an IOC value greater than 0.2. "Non-competing" immigrants are all other immigrants. Full-time employed workers are defined to be individuals working at least 48 weeks in the past year, averaging at least 30 hours, and being paid a wage at least as large as the minimum wage. All standard errors are clustered at the MSA-level. * p<0.1; ** p<0.05; and *** p<0.01

Table 6: IV Estimates using Different Instruments

		IV Estimates			
		2000 Census		1990 Census	
	OLS	College-Educated Immigrants	All Immigrants	College-Educated Immigrants	All Immigrants
	(a)	(b)	(c)	(d)	(e)
Panel 1: Employment Probabilities					
Equation 1:					
Inflow Rate of All Immigrants	0.08*	0.16***	0.16**	0.20***	0.21**
	(0.04)	(0.05)	(0.06)	(0.07)	(0.08)
Equation 2:					
Inflows of Competing Immigrants	-0.06	0.07	0.07	0.07	0.04
	(0.16)	(0.22)	(0.25)	(0.35)	(0.41)
Inflows of Noncompeting Immigrants	0.11**	0.18*	0.18	0.23	0.25
	(0.05)	(0.10)	(0.11)	(0.14)	(0.16)
Panel 2: Full-Time Employment Probabilities					
Equation 1:					
Inflow Rate of All Immigrants	0.02	0.07	0.09	0.09	0.12
	(0.07)	(0.08)	(0.09)	(0.10)	(0.11)
Equation 2:					
Inflows of Competing Immigrants	-0.64**	-0.75**	-0.79*	-0.91*	-0.94
	(0.24)	(0.37)	(0.43)	(0.53)	(0.62)
Inflows of Noncompeting Immigrants	0.17**	0.27**	0.30*	0.32**	0.37*
	(0.08)	(0.13)	(0.15)	(0.16)	(0.19)
Panel 3: Earnings of All Employed Workers					
Equation 1:					
Inflow Rate of All Immigrants	0.18	0.17	0.22	0.03	0.10
	(0.15)	(0.22)	(0.25)	(0.27)	(0.32)
Equation 2:					
Inflows of Competing Immigrants	-0.83**	-1.04***	-1.16***	-1.28*	-1.46*
	(0.35)	(0.35)	(0.39)	(0.73)	(0.81)
Inflows of Noncompeting Immigrants	0.41**	0.45*	0.54*	0.34	0.45
	(0.18)	(0.24)	(0.29)	(0.32)	(0.38)
Panel 4: Earnings of Full-time Employed Workers					
Equation 1:					
Inflow Rate of All Immigrants	0.26*	0.28	0.32	0.18	0.23
	(0.15)	(0.21)	(0.23)	(0.25)	(0.30)
Equation 2:					
Inflows of Competing Immigrants	-0.35	-0.60**	-0.80**	-0.84	-1.13
	(0.25)	(0.29)	(0.36)	(0.61)	(0.74)
Inflows of Noncompeting Immigrants	0.41**	0.49**	0.58**	0.42	0.54
	(0.18)	(0.24)	(0.28)	(0.30)	(0.37)
First Stage F-Statistic					
Equation 1:					
Inflows of All Immigrants		37.9	15.6	7.7	6.4
Equation 2:					
Inflows of Competing Immigrants		16.4	8.6	4.7	3.8
Inflows of Noncompeting Immigrants		23.9	13.3	6.1	5.4

Notes: The different instruments use different samples (in the ACS and past Census') to compute the previous settlement patterns of earlier arriving immigrants. See notes in Table 3 for more information. All standard errors are clustered at the MSA level with N=840 for all regressions. * $p<0.1$; ** $p<0.05$; and *** $p<0.01$

Table 7: Robustness Tests of IV Analysis

	Baseline	Alternate Immigrant Inflow Measure	Exclude Demographic Covariates	Include Double Majors	Alternate Competing Definition: IOC>0.53	Alternate Competing Definition: IOC>0.00	Nine College Majors	Include Less-Educated Immigrants
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Panel 1: Employment Probabilities								
Equation 1:								
Inflow Rate of All Immigrants	0.16***	0.25**	0.15***	0.15***	0.16***	0.16***	0.17***	0.22***
	(0.05)	(0.10)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.08)
Equation 2:								
Inflows of Competing Immigrants	0.07	0.14	0.03	0.06	0.08	0.16	0.05	0.20
	(0.22)	(0.23)	(0.23)	(0.20)	(0.23)	(0.18)	(0.20)	(0.42)
Inflows of Noncompeting Immigrants	0.18*	0.28**	0.18*	0.17*	0.17*	0.16	0.19**	0.41*
	(0.10)	(0.13)	(0.10)	(0.10)	(0.10)	(0.11)	(0.07)	(0.23)
Inflows of Less-Educated Immigrants								-0.10
								(0.11)
Panel 2: Full-Time Employment Probabilities								
Equation 1:								
Inflow Rate of All Immigrants	0.07	0.10	0.09	0.05	0.07	0.07	0.07	0.09
	(0.08)	(0.13)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.12)
Equation 2:								
Inflows of Competing Immigrants	-0.75**	-0.78**	-0.77**	-0.63	-0.73**	-0.47	-0.71*	-1.54*
	(0.37)	(0.34)	(0.38)	(0.39)	(0.36)	(0.33)	(0.40)	(0.81)
Inflows of Noncompeting Immigrants	0.27**	0.34**	0.29**	0.22	0.26**	0.24*	0.22**	0.57**
	(0.13)	(0.16)	(0.13)	(0.14)	(0.13)	(0.14)	(0.10)	(0.26)
Inflows of Less-Educated Immigrants								-0.10
								(0.25)
Panel 3: Earnings of All Employed Workers								
Equation 1:								
Inflow Rate of All Immigrants	0.17	0.19	0.29	0.15	0.17	0.17	0.15	0.35
	(0.22)	(0.32)	(0.26)	(0.21)	(0.22)	(0.22)	(0.20)	(0.32)
Equation 2:								
Inflows of Competing Immigrants	-1.04***	-1.02*	-0.68*	-0.90**	-1.08***	-0.74**	-0.99**	-1.82**
	(0.35)	(0.54)	(0.36)	(0.44)	(0.35)	(0.32)	(0.39)	(0.78)
Inflows of Noncompeting Immigrants	0.45*	0.51	0.53*	0.40	0.45*	0.44	0.37*	1.35*
	(0.24)	(0.31)	(0.27)	(0.26)	(0.25)	(0.27)	(0.20)	(0.76)
Inflows of Less-Educated Immigrants								-0.52
								(0.44)
Panel 4: Earnings of Full-time Employed Workers								
Equation 1:								
Inflow Rate of All Immigrants	0.28	0.38	0.40	0.28	0.28	0.28	0.25	0.54*
	(0.21)	(0.31)	(0.25)	(0.20)	(0.21)	(0.21)	(0.18)	(0.31)
Equation 2:								
Inflows of Competing Immigrants	-0.60**	-0.50	-0.26	-0.55	-0.65**	-0.44*	-0.46	-0.65
	(0.29)	(0.42)	(0.31)	(0.36)	(0.30)	(0.25)	(0.39)	(0.67)
Inflows of Noncompeting Immigrants	0.49**	0.62*	0.55**	0.48*	0.50**	0.50*	0.39**	1.49*
	(0.24)	(0.33)	(0.26)	(0.26)	(0.24)	(0.26)	(0.18)	(0.78)
Inflows of Less-Educated Immigrants								-0.61
								(0.47)

Notes: All regressions, except those in Column (h), are restricted to native and immigrant college graduates. The estimates in Column (h) also include inflows of non-College educated immigrants, which changes the denominator in the inflow rate variable and now also includes non-college educated natives and immigrants. Thus, one cannot simply compare the magnitudes of these coefficients with the coefficients in the other columns, even if one can compare the signs and statistical significance. All regressions use the baseline instrumental variable approach, all cluster standard errors at the MSA level, and all have N=840. * $p<0.1$; ** $p<0.05$; and *** $p<0.01$

Table 8: IV Estimates using Occupational Employment

	Occupation-Based Definition of Competing/Noncompeting			College Major-Based Definition of Competing/Noncompeting	
	All Immigrants	**Matching Immigrants**	**Non-matching Immigrants**	**Matching Immigrants**	**Non-matching Immigrants**
	(a)	(b)	(c)	(d)	(e)
Panel 1: Employment Probabilities					
Equation 1:					
Inflow Rate of All Immigrants	0.11	0.14*	0.10	0.50***	0.22***
	(0.09)	(0.08)	(0.09)	(0.17)	(0.08)
Equation 2:					
Inflows of Competing Immigrants	0.62**	0.25	0.40**	0.42	0.08
	(0.28)	(0.36)	(0.19)	(0.53)	(0.32)
Inflows of Noncompeting Immigrants	0.04	0.13	0.06	0.52*	0.26*
	(0.11)	(0.13)	(0.09)	(0.27)	(0.15)
Panel 2: Full-Time Employment Probabilities					
Equation 1:					
Inflow Rate of All Immigrants	-0.03	-0.03	-0.04	0.24	0.11
	(0.09)	(0.11)	(0.08)	(0.24)	(0.11)
Equation 2:					
Inflows of Competing Immigrants	0.35	-0.50	0.29	-2.20**	-1.06**
	(0.45)	(0.53)	(0.35)	(1.11)	(0.51)
Inflows of Noncompeting Immigrants	-0.09	0.04	-0.08	0.76**	0.38**
	(0.13)	(0.18)	(0.10)	(0.35)	(0.19)
Panel 3: Earnings of All Employed Workers					
Equation 1:					
Inflow Rate of All Immigrants	0.26	0.29	0.24	0.63	0.22
	(0.20)	(0.20)	(0.19)	(0.76)	(0.31)
Equation 2:					
Inflows of Competing Immigrants	-0.01	-1.48	0.38	-2.56*	-1.47***
	(0.58)	(1.11)	(0.58)	(1.31)	(0.51)
Inflows of Noncompeting Immigrants	0.30	0.55*	0.22	1.31*	0.64**
	(0.19)	(0.29)	(0.17)	(0.74)	(0.35)
Panel 4: Earnings of Full-time Employed Workers					
Equation 1:					
Inflow Rate of All Immigrants	0.33*	0.36**	0.30*	1.01	0.39
	(0.18)	(0.18)	(0.17)	(0.74)	(0.29)
Equation 2:					
Inflows of Competing Immigrants	0.22	-1.02	0.47	-1.08	-0.89**
	(0.55)	(1.03)	(0.43)	(0.74)	(0.43)
Inflows of Noncompeting Immigrants	0.34*	0.56**	0.27*	1.46**	0.71**
	(0.18)	(0.24)	(0.15)	(0.67)	(0.36)

Notes: The results in columns (a)-(c) use occupational employment to determine who is a competing and non-competing immigrant. Competing immigrants are immigrants employed in the same broad occupation group as natives. Non-competing immigrants are employed in a different occupation group. The eight broad occupation groups include: managers, business, computer, engineering, science, education, healthcare, and high-skill services. We exclude two other broad occupation groups, production (including construction and extraction) and other services, because more than half of the people working in these occupations do not have a college degree. Occupational matches for business majors include managerial and business occupations; for science majors include science occupations, for education majors include education occupations; for health majors include health occupations; for engineering majors include engineering occupations, for computer science majors include computer jobs, and for liberal arts majors include high-skill service jobs. All regressions cluster standard errors at the MSA level. N=960 (8 occupations*3 years* 40 MSAs) for columns (a)-(c) and N=840 for columns (d)-(e). * p<0.1; ** p<0.05; and *** p<0.

Table 9: IV Estimates of Demographic Subgroup Analysis

	Impacts by Age		**Impacts by Sex**	
	Younger Workers	**Older Workers**	**Men**	**Women**
	(a)	(b)	(c)	(d)
Panel 1: Employment Probabilities				
Equation 1:				
Inflow Rate of All Immigrants	0.22***	0.03	0.30***	0.26***
	(0.06)	(0.07)	(0.09)	(0.06)
Equation 2:				
Inflows of Competing Immigrants	-0.37	0.22	-1.16***	1.89***
	(0.25)	(0.32)	(0.31)	(0.42)
Inflows of Noncompeting Immigrants	0.35***	-0.01	0.63***	-0.11
	(0.10)	(0.13)	(0.13)	(0.12)
Panel 2: Full-Time Employment Probabilities				
Equation 1:				
Inflow Rate of All Immigrants	0.25**	-0.12	0.21	0.06
	(0.10)	(0.09)	(0.12)	(0.12)
Equation 2:				
Inflows of Competing Immigrants	-1.91***	-0.14	-1.64***	0.57
	(0.54)	(0.34)	(0.45)	(0.57)
Inflows of Noncompeting Immigrants	0.74***	-0.11	0.63***	-0.06
	(0.15)	(0.15)	(0.17)	(0.13)
Panel 3: Earnings of All Employed Workers				
Equation 1:				
Inflow Rate of All Immigrants	0.35	0.42	0.12	0.21
	(0.22)	(0.29)	(0.27)	(0.25)
Equation 2:				
Inflows of Competing Immigrants	-1.19*	-0.45	-0.68	-1.73**
	(0.65)	(0.48)	(0.45)	(0.78)
Inflows of Noncompeting Immigrants	0.71***	0.62**	0.31	0.66***
	(0.26)	(0.31)	(0.35)	(0.20)
Panel 4: Earnings of Full-time Employed Workers				
Equation 1:				
Inflow Rate of All Immigrants	0.44**	0.64**	0.32	0.45
	(0.22)	(0.26)	(0.23)	(0.28)
Equation 2:				
Inflows of Competing Immigrants	-0.52	-0.14	-0.55	-1.12
	(0.66)	(0.38)	(0.43)	(0.87)
Inflows of Noncompeting Immigrants	0.66**	0.81***	0.51*	0.81***
	(0.27)	(0.30)	(0.30)	(0.22)

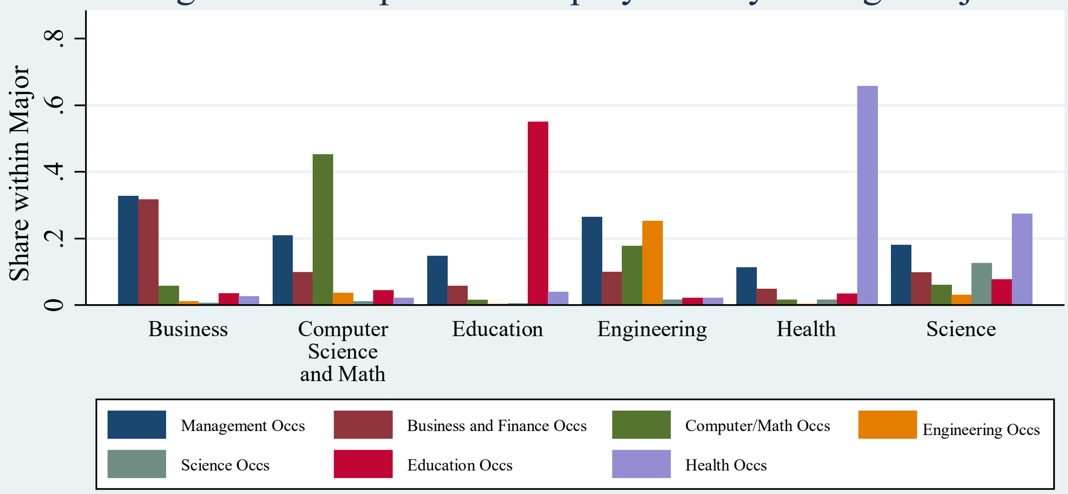
Notes: All regressions use the baseline instrumental variable approach, all cluster standard errors at the MSA level, and all have N=840. * $p<0.1$; ** $p<0.05$; and *** $p<0.01$

Table 10: IV Estimates by Industry Subgroup Analysis

	Immigrant-Intensive vs. Non-Intensive Industries		Local Service vs. Other Industries	
	Intensive Industries	**Non-Intensive Industries**	**Local Service Industries**	**Other Industries**
	(a)	(b)	(c)	(d)
Panel 1: Employment Probabilities				
Equation 1:				
Inflow Rate of All Immigrants	0.24***	0.19**	0.10	0.19***
	(0.08)	(0.09)	(0.07)	(0.06)
Equation 2:				
Inflows of Competing Immigrants	-0.05	-0.02	0.72**	-0.23
	(0.32)	(0.52)	(0.29)	(0.27)
Inflows of Noncompeting Immigrants	0.30***	0.24*	-0.04	0.29**
	(0.11)	(0.12)	(0.09)	(0.12)
Panel 2: Full-Time Employment Probabilities				
Equation 1:				
Inflow Rate of All Immigrants	0.15	0.06	0.14	0.10
	(0.12)	(0.10)	(0.18)	(0.10)
Equation 2:				
Inflows of Competing Immigrants	-0.79*	-0.71	0.89	-1.20***
	(0.45)	(0.79)	(0.85)	(0.42)
Inflows of Noncompeting Immigrants	0.37***	0.24	-0.04	0.41***
	(0.14)	(0.16)	(0.21)	(0.14)
Panel 3: Earnings of All Employed Workers				
Equation 1:				
Inflow Rate of All Immigrants	0.80***	-0.13	-0.21	0.55*
	(0.28)	(0.17)	(0.26)	(0.29)
Equation 2:				
Inflows of Competing Immigrants	-2.82***	-1.53*	-0.88	-1.93***
	(0.64)	(0.79)	(1.05)	(0.54)
Inflows of Noncompeting Immigrants	1.66***	0.21	-0.05	1.14***
	(0.32)	(0.28)	(0.24)	(0.38)
Panel 4: Earnings of Full-time Employed Workers				
Equation 1:				
Inflow Rate of All Immigrants	0.66**	-0.01	-0.20	0.53*
	(0.27)	(0.18)	(0.15)	(0.28)
Equation 2:				
Inflows of Competing Immigrants	-1.35**	-0.95	-0.05	-0.82
	(0.67)	(0.61)	(0.90)	(0.53)
Inflows of Noncompeting Immigrants	1.15***	0.22	-0.24	0.85**
	(0.38)	(0.26)	(0.23)	(0.40)

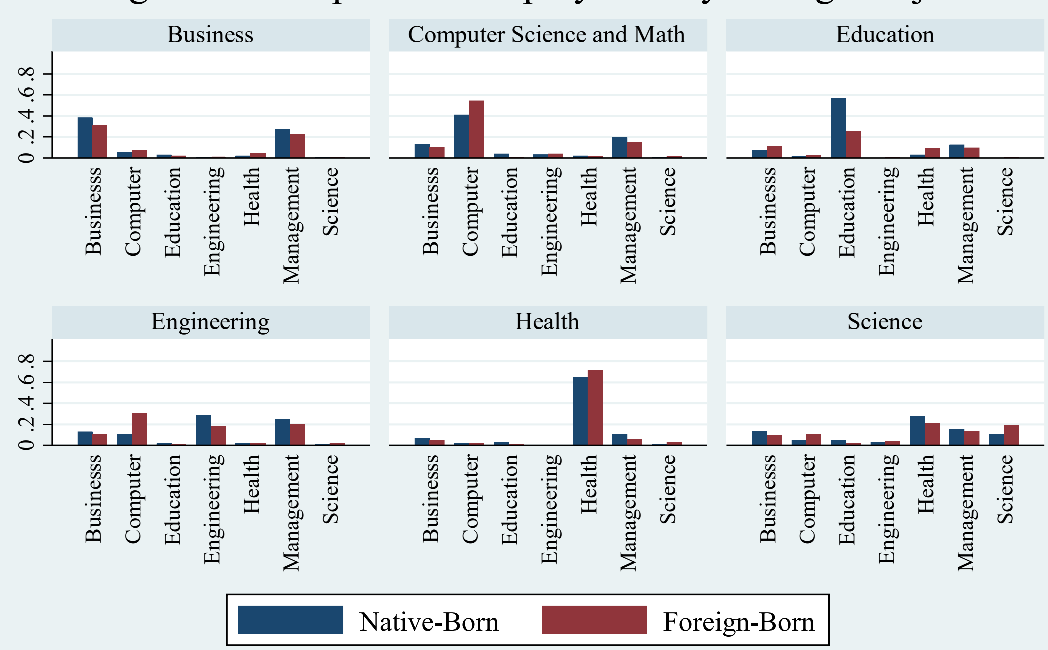
Notes: Immigrant-intensive industries include the industries with the highest proportion of college-educated immigrants. These include finance, professional services, healthcare, and information industries. Non-intensive industries include all other industries. The local service industries include construction, education, government, and utilities industries. Both classifications exclude manufacturing, agriculture and extraction, wholesale trade, retail trade, transportation, and other low-skill services. All regressions use the baseline instrumental variable approach, all cluster standard errors at the MSA level, and all have N=840. * p<0.1; ** p<0.05; and *** p<0.01

Figure 1: Occupational Employment by College Major



Note: This figure combines Healthcare Practitioner Occupations with Healthcare Support Occupations; and Business and Financial Operations Occupations with Sales Occupations. Arts and Entertainment Occupations, Grounds and Maintenance Occupations, Social Service Occupations, Construction and Extraction Occupations, Farming, Fishing, and Forestry Occupations, Food Preparation Occupations, Installation and Maintenance Occupations, Legal Occupations, Office and Administrative Support Occupations, Personal Care Service Occupations, Production Occupations, and Transportation Occupations are all excluded from this figure because they comprise a small proportions of employment among college graduates. Together these comprise less than 20 percent for all majors, except Business and Liberal Arts, where they represent 22 percent and 40 percent, respectively.

Figure 2: Occupational Employment by College Major



This Figure plots occupational employment by major and immigrantion status. See Figure 1 for details about the aggregation of occupations.

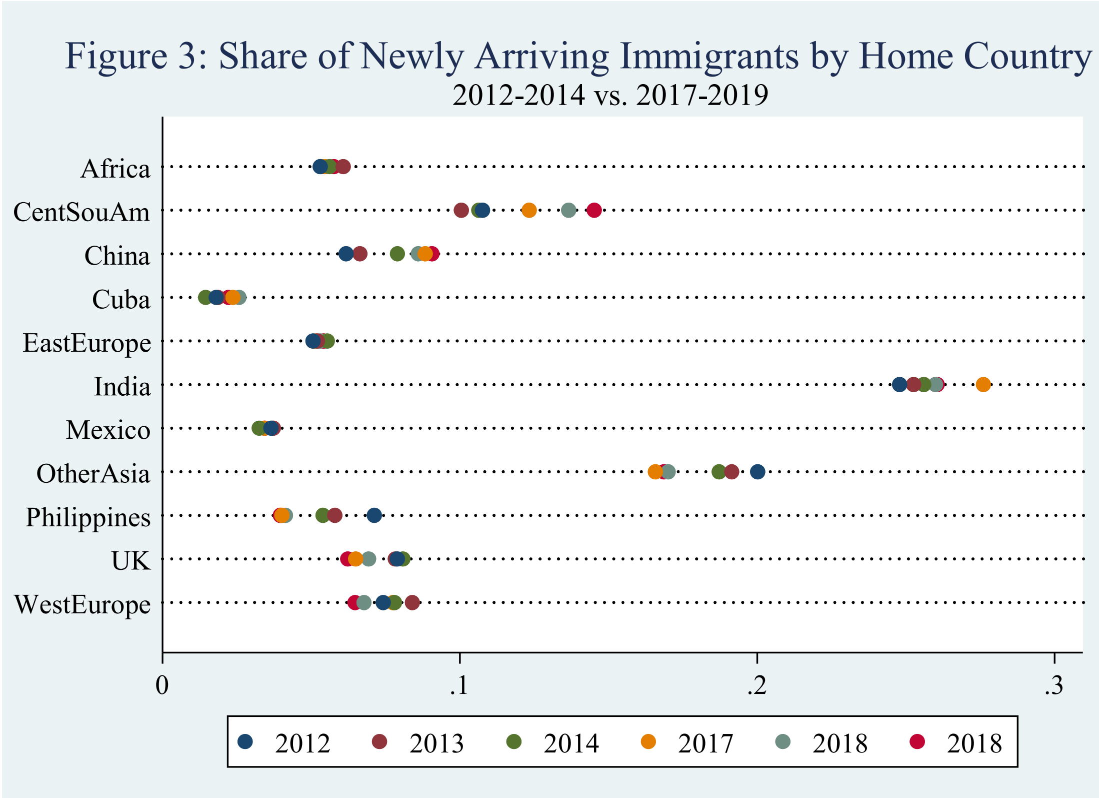
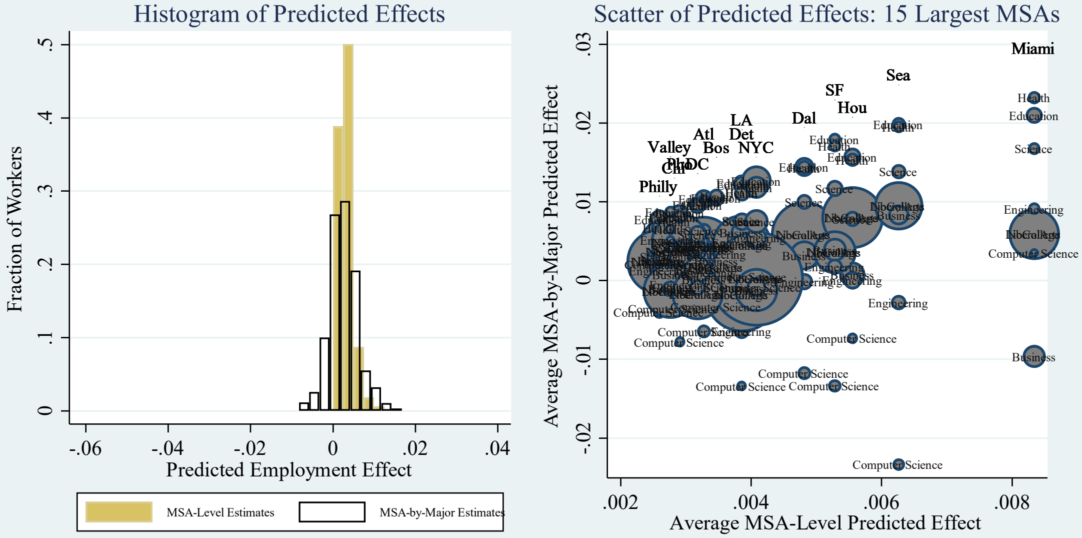


Figure 3: Share of Newly Arriving Immigrants by Home Country
2012-2014 vs. 2017-2019
Africa
CentSouAm
China
Cuba
EastEurope
India
Mexico
OtherAsia
Philippines
UK
WestEurope
0
.1
.2
.3
2012
2013
2014
2017
2018
2018

Figure 4: Predicted Effects on Full-Time Employment

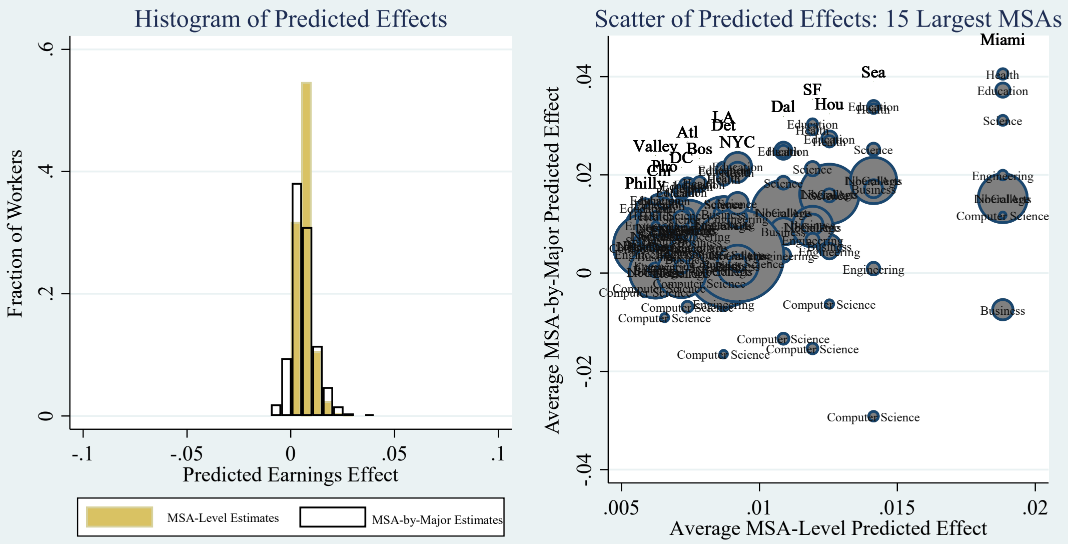
MSA-Level Estimates vs. Major-by-MSA Estimates



Notes: This figure uses the estimated effects of the impact of immigration inflows on full-time employment combined with the actual immigration inflows to plot the predicted impacts of immigration on full-time employment. The two plots compare the predicted effects when competing and non-competing immigrants are (MSA-by-Major Estimates) and are not (MSA-Level Estimates) accounted for.

Figure 5: Predicted Effects on Earnings

MSA-Level Estimates vs. Major-by-MSA Estimates



Notes: This figure uses the estimated effects of the impact of immigration inflows on employed earnings combined with the actual immigration inflows to plot the predicted impacts of immigration on earnings for all employed workers. The two plots compare the predicted effects when competing and non-competing immigrants are (MSA-by-Major Estimates) and are not (MSA-Level Estimates) accounted for.

ONLINE APPENDIX A: Additional Tables and Figures

Table A1: Groupings of Individual Majors

Business	**Engineering**	**Liberal Arts**	**Liberal Arts (Continued)**
Accounting	General Engineering	General Agriculture	United States History
Actuarial Science	Aerospace Engineering	Agriculture Production & Management	Human Services & Community Organization
Agricultural Economics	Biological Engineering	Miscellaneous Agriculture	Social Work
Business Economics	Architectural Engineering	Natural Resources Management	General Social Sciences
Business Management & Administration	Biomedical Engineering	Architecture	Anthropology & Archeology
Economics	Chemical Engineering	Area Ethnic & Civilization Studies	Criminology
Family & Consumer Sciences	Civil Engineering	Communications	Geography
Finance	Computer Engineering	Journalism	International Relations
General Business	Electrical Engineering	Mass Media	Political Science & Government
Hospitality Management	Engineering Mechanics Physics & Science	Advertising & Public Relations	Sociology
Human Resources & Personnel Mgmt	Military Technologies	Communication Technologies	Miscellaneous Social Sciences
International Business	Nuclear, Industrial Radiology, & Biotech	Cognitive Science & Biopsychology	History
Mgmt Information Systems & Statistics	Environmental Engineering	Fine Arts	Forestry
Marketing & Marketing Research	Geological & Geophysical Engineering	Drama & Theater Arts	
Miscellaneous Business & Medical Admin	Industrial & Manufacturing Engineering	Music	**Science**
Operations Logistics & E-Commerce	Materials Engineering & Materials Science	Visual & Performing Arts	Animal Sciences
	Mechanical Engineering	Commercial Art & Graphic Design	Food Science
Computer Science & Math	Metallurgical Engineering	Film Video & Photographic Arts	Plant Science & Agronomy
Computer & Information Systems	Mining & Mineral Engineering	Art History & Criticism	Soil Science
Computer Programming & Data Processing	Naval Architecture & Marine Engineering	Studio Arts	Environmental Science
Computer Science	Nuclear Engineering	Cosmetology Services & Culinary Arts	Biology
Information Sciences	Petroleum Engineering	Linguistics & Comparative Language & Lit	Biochemical Sciences
Computer Admin Management & Security	Miscellaneous Engineering	Foreign Language Studies	Botany
Computer Networking & Telecommunications	Ring Technologies	Other Foreign Languages	Molecular Biology
Mathematics	Engineering & Industrial Management	Court Reporting	Ecology
Applied Mathematics	Electrical Engineering Technology	Pre-Law & Legal Studies	Genetics
Statistics & Decision Science	Industrial Production Technologies	English Language & Literature	Microbiology
Mathematics & Computer Science	Mechanical Engineering Related Technologies	Composition & Speech	Pharmocology
	Miscellaneous Engineering Technologies	Liberal Arts	Physiology
Education	Construction Services	Humanities	Zoology
General Education	Electrical & Mechanic Repairs Technologies	Library Science	Miscellaneous Biology
Educational Administration & Supervision	Precision Production & Industrial Arts	Intercultural & International Studies	Neuroscience
School Student Counseling	Transportation Sciences & Technologies	Interdisciplinary Social Sciences	Physical Sciences
Elementary Education		Multi-Diciplinary Or General Science	Astronomy & Astrophysics
Mathematics Teacher Education	**Health**	Physical Fitness Parks Recreation & Leisure	Atmospheric Sciences & Meteorology
Physical & Health Education Teaching	General Medical & Health Services	Philosophy & Religious Studies	Chemistry
Early Childhood Education	Communication Disorders Sciences	Theology & Religious Vocations	Geology & Earth Science
Science & Computer Teacher Education	Health & Medical Administrative Services	Psychology	Geosciences
Secondary Te	Medical Assisting Services	Educational Psychology	Oceanography
Special Needs Education	Medical Technologies Technicians	Clinical Psychology	Physics
Social Science Or History Teacher Education	Health & Medical Preparatory Programs	Counseling Psychology	
Teacher Education: Multiple Levels	Nursing	Industrial & Organizational Psychology	
Language & Drama Education	Pharmaceutical Sciences & Administration	Social Psychology	
Art & Music Education	Treatment Therapy Professions	miscellaneous Social Sciences	
Miscellaneous Education	Community & Public Health	Criminal Justice & Fire Protection	
	Miscellaneous Us Health Medical Professions	Public Administration	
	Nutrition Sciences	Public Policy	

Table A2 - Average Immigrant Inflow Rates by MSA, 2017-2019

MSA Name	All Immigrants	Business	Computer Science	Engi-neering	Science	Health	Education	Liberal Arts
		Inflows of Competing Immigrants						
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
San Jose, CA	0.148	0.021	0.095	0.058	0.014	0.004	0.002	0.015
Miami, FL	0.114	0.040	0.027	0.021	0.014	0.007	0.010	0.024
Seattle, WA	0.086	0.014	0.046	0.025	0.009	0.004	0.003	0.013
Orlando, FL	0.083	0.024	0.023	0.016	0.011	0.005	0.006	0.020
Houston, TX	0.076	0.019	0.027	0.020	0.012	0.005	0.005	0.012
San Francisco, CA	0.072	0.015	0.032	0.017	0.008	0.002	0.002	0.016
Dallas, TX	0.066	0.014	0.029	0.018	0.008	0.003	0.003	0.012
Las Vegas, NV	0.061	0.020	0.011	0.007	0.010	0.006	0.004	0.016
New York, NY	0.056	0.016	0.016	0.009	0.007	0.003	0.002	0.015
Tampa, FL	0.056	0.015	0.018	0.011	0.007	0.004	0.005	0.010
Austin, TX	0.054	0.010	0.024	0.015	0.007	0.003	0.003	0.010
Los Angeles, CA	0.053	0.015	0.014	0.009	0.007	0.003	0.002	0.016
Detroit, MI	0.053	0.008	0.027	0.020	0.006	0.003	0.002	0.010
San Diego, CA	0.050	0.012	0.016	0.011	0.009	0.003	0.002	0.011
Boston, MA	0.047	0.010	0.016	0.009	0.008	0.002	0.002	0.011
Atlanta, GA	0.045	0.012	0.018	0.011	0.006	0.002	0.002	0.008
Washington, DC	0.044	0.010	0.012	0.007	0.006	0.002	0.002	0.013
Charlotte, NC	0.041	0.009	0.020	0.013	0.005	0.002	0.001	0.006
Sacramento, CA	0.041	0.008	0.013	0.009	0.008	0.004	0.002	0.010
Jacksonville, FL	0.040	0.014	0.012	0.006	0.007	0.005	0.001	0.006
Phoenix, AZ	0.040	0.007	0.018	0.011	0.006	0.003	0.002	0.006
Chicago, IL	0.039	0.009	0.014	0.008	0.006	0.003	0.002	0.007
Riverside, CA	0.038	0.011	0.008	0.005	0.006	0.004	0.001	0.011
Portland, OR	0.037	0.007	0.014	0.010	0.005	0.002	0.003	0.008
Columbus, OH	0.037	0.006	0.019	0.012	0.004	0.001	0.001	0.006
Philadelphia, PA	0.036	0.007	0.013	0.008	0.006	0.003	0.002	0.007
Nashville, TN	0.035	0.007	0.013	0.008	0.006	0.002	0.002	0.007
San Antonio, TX	0.034	0.005	0.014	0.009	0.007	0.004	0.003	0.004
Indianapolis, IN	0.031	0.007	0.011	0.008	0.006	0.002	0.003	0.005
Providence, RI	0.030	0.008	0.010	0.008	0.003	0.001	0.002	0.007
Cincinnati, OH	0.029	0.008	0.013	0.007	0.003	0.001	0.002	0.004
Baltimore, MD	0.029	0.006	0.008	0.004	0.007	0.002	0.002	0.007
Minneapolis, MN	0.028	0.005	0.011	0.008	0.005	0.001	0.002	0.005
Denver, CO	0.024	0.005	0.009	0.006	0.003	0.001	0.001	0.006
St. Louis, MO	0.023	0.003	0.009	0.004	0.006	0.002	0.001	0.004
Virginia Beach, VA	0.023	0.005	0.007	0.004	0.004	0.003	0.001	0.005
Cleveland, OH	0.023	0.003	0.009	0.006	0.006	0.002	0.001	0.004
Pittsburgh, PA	0.022	0.003	0.011	0.008	0.003	0.001	0.001	0.004
Milwaukee, WI	0.021	0.005	0.009	0.006	0.002	0.001	0.001	0.004
Kansas City, MO	0.019	0.003	0.008	0.005	0.003	0.001	0.001	0.004

This table presents the average five year inflow rate of all immigrants into each MSA (column a) as well as the five-year inflow rate of competing immigrants for each major in each MSA (columns b-h). The non-competing inflow rate is simply the column (a) value minus the competing inflow rate for each major-by-MSA.

Table A3: Average Change in Immigrant Country of Origin

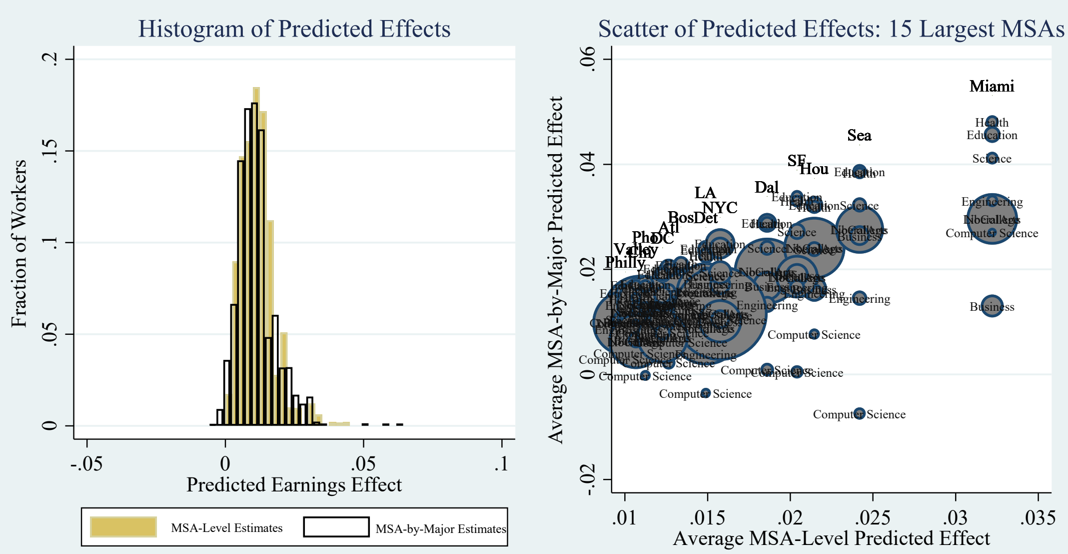
2012-2014 to 2017-2019 by Major

	College Major							
Country of Origin	Full Sample	Business	Computer Science	Engineering	Science	Health	Education	Liberal Arts
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Central/South America	3.0%	4.0%	1.2%	3.1%	2.8%	2.4%	4.7%	3.4%
China	1.9%	2.8%	0.8%	2.1%	1.0%	1.1%	1.2%	2.3%
India	1.3%	0.4%	1.3%	1.1%	0.8%	-2.2%	-0.1%	0.0%
Cuba	0.7%	0.6%	0.6%	0.4%	0.0%	2.6%	1.4%	1.0%
EastEurope	0.0%	0.3%	0.5%	-0.5%	-0.6%	-0.3%	-0.3%	0.6%
Mexico	0.0%	-0.8%	-0.1%	0.4%	0.2%	0.6%	1.5%	-0.1%
Africa	-0.2%	0.0%	-0.3%	0.0%	1.1%	-0.3%	-0.4%	-0.3%
WestEurope	-0.9%	-1.0%	-0.4%	-0.4%	-2.8%	0.2%	0.4%	-0.9%
UK	-1.4%	-1.1%	-1.0%	-1.2%	-1.2%	-0.5%	-1.7%	-1.7%
Philippines	-2.1%	-3.2%	-1.6%	-1.2%	0.1%	-5.7%	-3.1%	-1.0%
OtherAsia	-2.5%	-2.0%	-0.9%	-3.7%	-1.2%	2.1%	-3.6%	-3.2%

Notes: This table plots the average change in immigrant share for each major (and overall) by country of origin, where the numbers represent the change in the average inflow share in 2017-2019 relative to 2012-2014.

Figure A1: Predicted Effects on Full-Time Earnings

MSA-Level Estimates vs. Major-by-MSA Estimates



Notes: This figure uses the estimated effects of the impact of immigration inflows on full-time earnings combined with the actual immigration inflows to plot the predicted impacts of immigration on earnings for full-time employed workers. The two plots compare the predicted effects when competing and non-competing immigrants are (MSA-by-Major Estimates) and are not (MSA-Level Estimates) accounted for.