High-Skilled Immigration and the Labor Market: Evidence from the H-1B Visa Program*

Patrick S. Turner†
Department of Economics
University of Notre Dame

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Abstract

This paper investigates the effect of high-skilled immigration on the wages of U.S.-born college graduates. Descriptive evidence suggests that workers with different college majors compete in separate labor markets. Because immigrants are more likely than natives to study science, technology, engineering and mathematics (STEM), a standard labor market model predicts that the relative wages of native STEM majors should fall as skilled immigration increases. Using an IV strategy that leverages large changes in the cap of H-1B visas and controls for major- and age-specific unobservable characteristics, I find that workers most exposed to increased competition from immigration have lower wages than one would expect. A 10 percentage point increase in a skill group's immigrant-native ratio decreases their relative wages by 1.2 percent. Overall, I estimate that the STEM wage premium decreased 4–12 percentage points from 1990–2010 because of immigration.

JEL Classification: F22, J31, J61

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†Contact: Department of Economics, University of Notre Dame, 3030 Jenkins-Nanovic Hall, Notre Dame, IN 46556. E-mail: Patrick.Turner@ND.edu

1 Introduction

Increasing the size of the science, technology, engineering, and mathematics (STEM) workforce has been a key strategy to maintain the economic competitiveness and growth of the U.S. economy. STEM workers have specialized skills that support research and development activities, increasing the productivity of all workers in the economy (Rothwell et al., 2013). Indeed, adding to the STEM workforce increases patenting across cities and firms (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Winters, 2014). Attempts to increase the home-grown STEM workforce, however, have proven to be challenging amid concerns of poor mathematics preparation upon entering college and high attrition after introductory courses (President's Council of Advisors on Science and Technology, 2012). Immigration policy offers an alternative. Changes to temporary visa programs, such as increasing the annual cap on the H-1B, can increase the number of STEM workers, and these workers tend to be more productive (Hunt, 2011). While there is growing empirical evidence on the effects of H-1B immigration on regions and firms (e.g., Peri et al., 2015; Doran et al., 2016), less is known about the distributional impacts of skilled immigration policy across workers with different types of skills.

In this paper, I investigate the effect that immigration has on the wages of college-educated U.S.-born natives. Current U.S. high-skilled immigration policy disproportionately increases the STEM workforce compared to the increase among other college-educated workers. While immigrants represent about 17 percent of the U.S. adult population with a bachelor's degree, they comprise nearly 29 percent of college graduates with a STEM major.[1] I present descriptive evidence that workers with different college majors are imperfect substitutes, which implies that they are distinct factors of production. Because high-skilled immigration changes the relative supplies of different types of workers, the relative wages of workers who are most similar to immigrants should fall.

I estimate the relationship between immigration and relative wages by taking advantage of recently available data on the college major of bachelor's degree holders in the U.S. and large changes in the annual cap of the H-1B visa program. Using data from the 2010–2012 American Community Survey, I categorize workers into tightly defined skill groups based on their college major and their U.S. labor market experience. Because the endogenous arrival of immigrants confounds OLS estimation, I construct an instrument of the number of immigrants with particular majors across different labor market cohorts using the cap of H-1B visas in the year cohorts entered the U.S. labor market combined with the fact that visa recipients are more likely to be STEM majors. I estimate an instrumental variable (IV) model relating average log earnings to the relative size of immigrant inflows with college major and cohort fixed effects. This specification thus compares the wages of native workers with the same college major across cohorts with differently sized labor

[1]Based on author's calculations from the 2010-2012 American Community Survey.

supply increases due to H-1B cap policy, while controlling non-parametrically for the national wage-experience profile.

I find that workers who are most exposed to increased competition from high-skilled immigration, STEM majors, have lower wages than one would expect given their age and college major. Specifically, I measure immigrant competition as the immigrant-native ratio within a major-experience skill group. My results suggest that a 10 percentage point increase in the immigrant-native ratio within a major-experience group lowers relative wages by 1.2 percent. Computer Science majors experienced the largest changes in this variable across experience cohorts, a 50 percentage point increase between the 1990 and 2000 cohorts. Because immigrants arrive and stay in the U.S. when returns to their skills are high, OLS is upward biased. Notably, a negative effect only appears after correcting for the endogeneity of immigration. This finding is consistent with an endogeneity bias, and the IV reveals the negative effect predicted by the theoretical model. Further, I present evidence that the adverse wage effect occurs alongside occupational switching of native-born workers. Using data on occupation-specific tasks from the O*NET database, I find that natives are more likely to work in occupations where interactive tasks are more important than quantitative tasks for their job.

I also address the broader question of how immigration from 1990 to 2010 has affected STEM wages overall. My empirical strategy is not well suited to answer this question because of the reduction of sample size when focusing on STEM and non-STEM majors in the aggregate. The theoretical model, however, provides a simple relationship between immigration-based increases in the labor supply of STEM and non-STEM workers and the STEM wage premium. Crucially, this relationship depends on the elasticity of substitution between these workers. To my knowledge, this elasticity has not been estimated in the literature. I provide estimates that fall within the theoretical bounds of this parameter set by the elasticities nested above and below college major. Using my estimates, I simulate changes in the STEM wage premium and find that STEM wages fell 4–12 percent relative to non-STEM wages because of immigration over the period.

This paper thus provides a new insight into the labor market effects of increasing the STEM workforce by highlighting the distributional consequences of altering the skill mix of the labor force. Because the wages of STEM workers are higher on average, immigration-based increases in the STEM workforce reduce wage inequality among college graduates. Additionally, STEM degree completion rates among natives could fall if students respond to changes in the STEM wage premium or if immigration policy increases within-classroom competition from foreign peers. The effect of immigrant competition in the labor market on native STEM major choice appears to be small and isolated to particular subgroups (Orrenius and Zavodny, 2015; Ransom and Winters, Forthcoming), but the presence of foreign peers in early mathematics courses reduces the likelihood that natives complete a STEM degree (Anelli et al., 2017).

This paper also contributes to the broad literature exploring the effects of immigration on the wages of native workers. The degree to which immigration depresses the wages of natives has been a contentious subject among academics and in the popular press. The question of which workers compete most intensely with immigrants lies at the center of the debate. For example, one notable disagreement centers on whether immigrant high school dropouts compete only with native high school dropouts or more broadly with high school graduates (Borjas, 2003; Borjas and Katz, 2007; Card, 2009; Lewis, 2017). This paper overcomes this type of concern by explicitly considering groups of workers who almost certainly compete in distinct labor markets. College graduates enter the workforce with different human capital depending on their field of study, and immigrants tend to study different subjects than natives. Furthermore, conditioning on field of study overcomes estimation challenges presented by using occupations (e.g., Card, 2001). There is substantial evidence that natives respond to immigration by switching occupations (Peri and Sparber, 2009, 2011), whereas a worker's college major is largely determined by the time they enter the labor force.

By focusing on tightly defined yet large skill groups, I find empirical evidence that increases in relative supplies lead to negative changes in relative wages. These results are consistent with other papers finding negative labor market effects among workers defined by their field of study or type of work (Borjas and Doran, 2012; Federman et al., 2006; Kaestner and Kaushal, 2012). Compared to those settings, the skill groups in this paper represent a much larger share of the total workforce. The empirical results of this paper are also consistent with structural work that finds that wages of native computer scientists would have been higher in the absence of growing skilled immigration in the 1990s (Bound et al., 2015, 2017; Khanna and Morales, 2017). Finally, the results complement Peri et al. (2015) who find positive wage effects of skilled immigration over a similar period. By making geographic comparisons, they identify the overall wage effect of immigration on all college-educated natives, rather than the distributional effect estimated here.

Additionally, this paper explores an important way in which natives and immigrants with the same skills, as measured by educational attainment and experience, are imperfectly substitutable (Ottaviano and Peri, 2012; Manacorda et al., 2012). I provide a novel explanation: differences in educational human capital within skill groups. This paper shows how large differences in the college major distribution of natives and immigrants might explain native-immigrant complementarity. This advances our understanding because, previously, language and task-specialization have been offered as potential explanations (Lewis, 2013; Peri and Sparber, 2009, 2011). These explanations seem better suited for low-skilled workers, while there is some evidence that the complementarity is stronger among high-skilled workers (Card, 2009). For college-educated workers, much of any observed imperfect substitution likely results from differences in the college major distribution of immigrants relative to natives. The degree of substitutability between a historian and a computer programmer is seemingly smaller than two computer programmers from different countries.

The paper proceeds as follows. Section 2 presents descriptive evidence that workers with different college majors compete in separate labor markets. I incorporate this stylized fact into the workhorse model used to analyze relative wages in the labor market. I then discuss the features of the H-1B visa program used to isolate exogenous variation in the stock of immigrants in the U.S. Section 3 describes the data and estimation strategy used to identify the causal effect of immigration on relative wages. Section 4 presents empirical results showing that the relative wages of groups with large immigrant inflows fall. Section 5 calibrates the theoretical model to quantify the broader effect of immigration on the STEM wage premium. Section 6 discusses implications of the findings.

2 Framework and Background

A standard labor demand model predicts that immigration affects relative wages if newly arriving immigrants alter the skill mix of the workforce. In the model, workers supply heterogenous labor inputs defined by their skill type. Different skill types (e.g., education and experience interactions) are combined into a labor aggregate using a set of nested constant elasticity of substitution (CES) functions. Groups of workers with the same skill type are assumed to be perfect substitutes, but are imperfectly substitutable with workers across groups. That is, workers in different groups have complementary skills and compete in segregated labor markets. Relative wages for a skill group will fall if immigrants are overrepresented in that group.

Researchers disagree on how to define skill groups so that they encompass perfectly substitutable workers. While it is widely agreed that college graduates and workers with no more than a high school are imperfect substitutes, immigration has not altered the skill mix along this dimension over the past five decades (Figure 1). The share of immigrants in the adult population has tracked closely to the share of immigrants among the college-educated, demonstrating that immigrants have not been overrepresented among either broad skill group. Therefore, immigration will only affect relative wages if there is imperfect substitutability among low-educated or high-educated groups. The literature has focused on whether high school dropouts and high school graduates are imperfect substitutes (e.g., Borjas, 2003, 2014) or instead are perfect substitutes that supply different levels of efficiency units (e.g., Katz and Murphy, 1992; Autor et al., 1998; Card and Lemieux, 2001; Card, 2009). This paper sidesteps that debate and focuses on imperfect substitutability among college-educated workers. As Figure 1 demonstrates, college-educated immigrants have historically been overrepresented in STEM occupations and this overrepresentation has been increasing.

2.1 Measuring the Impact of Immigration Using College Major

The key motivation for this paper is that, because of differences in major choice, not all college graduates enter the labor market with the same set of skills and therefore participate in different labor markets. For example, it is unlikely that computer programmers and historians are perfect substitutes in production. Under this assumption, immigration has the potential to affect relative wages if foreign-born workers study different fields than native-born workers. This subsection documents large overrepresentation of immigrants in STEM fields and presents descriptive evidence that skill groups stratified by college major characterize distinct labor inputs.

Immigrants and U.S.-born workers tend to major in different fields. Table 1 shows the distribution of college majors for the working-age population in the United States from 2010–2012 separately for natives (column 1) and immigrants (column 2). Strikingly, immigrants are nearly twice as likely to have studied a STEM field (35.3% to 17.6%). This pattern holds for both men (49.7% to 26.4%) and women (21.8% to 9.9%). Conditional on studying in a non-STEM field, immigrants are overrepresented in Business and Healthcare and underrepresented in Social Sciences and Education.

Workers with the same college major are more likely to compete in the same labor market. Table 2 shows that occupations become more concentrated as the definition of skill group becomes more tightly defined.[2] Panel A considers the aggregate shares of the five largest occupations within a particular skill group. I vary the definition of a skill group by constructing measures for (i) all workers, (ii) only college-educated workers, and (iii) each college major. As a skill group begins to include individuals that are more substitutable, occupational concentration should increase. Indeed, the data demonstrate this pattern. Twenty-two percent of all workers work in the five largest occupations. This share is increased to 37 percent when calculated for college-educated workers. I then calculate this share separately for each of forty college majors and find that, on average, about half of workers with a particular college major worked in five occupations. The fact that occupations become more concentrated within a college major suggests that workers grouped in this way are more substitutable.

Another useful measure in considering worker substitutability is the index of similarity. This measure compares the degree to which the occupational distributions of two separate groups overlap (Borjas and Doran, 2012). Groups with substantial overlap are more likely to be substitutable. Consider two groups i and j working in different occupations k, the index of similarity for these

[2] Occupations are defined by a worker's three-digit Standard Occupational Classification (SOC) code and the sample used is all working-age adults in the 2010–2012 ACS, not living in group quarters, that have a valid SOC code. Section 3.1 discusses how degree fields in the ACS are classified into majors.

two groups is defined by:

$$I_{ij} = 1 - \frac{1}{2}\sum_{k} |s_{ik} - s_{jk}| \tag{1}$$

where s_{ik} represents the share of group i in occupation k. The measure takes on values between 0 and 1, where the former represents no distributional overlap and the latter represents identical distributions. The complement of the index represents the proportion of one group that would have to change occupations in order for the groups to have the same distribution.

Panel B of Table 2 presents the index of similarity between different groups. The first row of Panel B shows the index of similarity between college and non-college educated workers. The value of 0.45 indicates that 55 percent of non-college educated workers would need to change their occupation in order for college and non-college workers to have the same distribution. The second row presents the average index of similarity when comparing the distribution of each major to all other majors and the final row compares natives to immigrants within each major. As workers are grouped into more tightly defined skill groups, the index of similarity should increase. Indeed, the index of similarity between college educated individuals (0.65) and workers with the same college major (0.80) demonstrates this pattern. Again, the pattern of increasing occupational overlap suggests that dividing college-educated workers into college major groups is likely to increase within-group substitutability.

Stratifying skill groups by college major has a particular advantage over using occupation. While it is feasible to categorize skill groups using occupations directly, this approach is not appropriate in the current setting. There is substantial evidence that natives respond to immigration by switching occupation (e.g., Peri and Sparber, 2009, 2011) and this endogenous response presents challenges in estimating the causal effect of immigration on wages.[3] Conversely, college major is largely a predetermined characteristic once workers enter the labor force and is less responsive to immigration. While there is the potential that workers return to school to earn a bachelor's in a new field or pursue graduate studies, the majority of graduates complete their Bachelor's degree when 22–23 (Spreen, 2013) and there seems to be a strong link between undergraduate and graduate fields (Altonji et al., 2015).

This discussion directly informs the empirical approach needed to measure the relative impact of immigration among differently-skilled college graduates. Consider the wage w_{mx} of a group of native-born workers with major m and experience level x. The following model relates log wages

[3]This concern was present in Card (2001) who probabilistically assigns workers to occupations using individual time-invariant characteristics.

to labor supply increases from immigration:[4]

$$\ln w_{mx} = \psi_m + \nu_x + \beta p_{mx} + \epsilon_{mx}, \tag{2}$$

where $p_{mx} = dL_{mx}/L_{mx}$ is the supply shock to major m and experience group x and $dL_{mx} = M_{mx}$ is the number of immigrants added to a major-experience group with (N_{mx}) natives. ψ_m and ν_x are major and cohort fixed effects that capture differences in average wages across majors and experience. Thus, the corresponding regression compares log wages of the group to the relative supply increase due to immigration and β is expected to be negative.

However, estimating Equation 2 with OLS will not identify the causal effect of immigration on wages. Immigrants enter and stay in the U.S. when demand for their skills is high. This endogeneity means that OLS is biased away from finding the negative effect predicted by the theory, a result demonstrated in recent work by Llull (2018). Thus, an instrument is needed to predict immigrant entry that is not related to skill-specific labor demand shocks. To overcome this challenge, I rely on large changes in the cap of H-1B visas – a temporary visa that brings skilled workers with specialty occupations to the U.S. – to generate policy variation in immigrant competition that differentially affected workers both across majors and cohorts.

2.2 The H-1B Visa Instrument

The H-1B visa is an important pathway for educated immigrants to enter the U.S. for work, making programmatic-changes over time a potential source of variation for an instrument. Of the nearly one million immigrants that are granted legal permanent residency in the U.S. each year, roughly 15 percent enter on an employment-based visa. Individuals adjusting from an H-1B visa to legal permanent residency make up a large share of employment-based visas. More than 80 percent of approved employment-based visas are awarded to individuals already in the U.S. on temporary visas (DHS, Yearbook of Immigration Statistics 2015) and H-1B visas make up nearly 50 percent of temporary work visas (Hunt, 2017).[5] These descriptive facts suggest that historic inflows of H-1B immigrants are related to the current stock of skilled immigrants.

The H-1B is a nonimmigrant visa providing foreigners the ability to work temporarily in the U.S. for a period of three years, renewable once for a total of six years. In a given year, there is a maximum number of available H-1B visas, although visa issuances can exceed that number due to

[4]This model is similar to the skill-group approach proposed by Borjas (2003, 2014). See Appendix C for a theoretical motivation.

[5]Other nonimmigrant visas exist which allow skilled workers to enter the U.S for employment reasons, but the H-1B visa is the most prominent. The L-1 visa allows multinational firms to transfer workers from an international office on a temporary basis and the TN visa is similar to the H-1B, but restricted to NAFTA countries and is not a dual intent visa.

exemptions for universities and non-profit organizations, visa renewals, and employer changes. The visa is awarded to firm-sponsored workers in "specialty occupations" that require specialized skills and at least a bachelor's degree. Visa holders work primarily in information technology occupations, such as computer programmers and software engineers, and many H-1B workers arrive from India and China (Kerr and Lincoln, 2010). Two features of the program allow for plausibly exogenous variation in the number of immigrants across majors and experience cohorts: changes in the cap and the fact that visa recipients tend to work in STEM related fields.

The Immigration Act of 1990 (IA90) introduced an annual cap of 65,000 visas in 1990 and the program has experienced a number of changes since that time. The cap is set for a given fiscal year, which begins in October, and the application period begins in the preceding April. The American Competitiveness and Workforce Improvement Act temporarily increased the cap to 115,000 for fiscal years 1999 and 2000. In 2000, the American Competitiveness in the 21st Century Act (AC21) further increased the cap to 195,000 for fiscal years 2001 through 2003. In the following year, the expansion was allowed to expire by Congress and the cap returned to 65,000. Finally, in 2006, an additional 20,000 slots were added for workers with an advanced degree from a U.S. university via the H-1B Visa Reform Act of 2004.[6] The top panel of Figure 2 summarizes the cap levels from 1990–2008 (solid line). While the cap was not binding in the early 1990s, it was for a number of years later in the decade and has been since the cap decreased in 2004 (Kerr and Lincoln, 2010).

Most H-1B visa applications are for work in STEM occupations. To receive an H-1B visa, firms sponsor specific individuals to work in the U.S. and file an application on their behalf. Firms must complete a Labor Condition Application (LCA) with the Department of Labor, which specifies the job, salary, length, and geographic location of employment for the position to be filled by the visa recipient. The LCA data are publicly available and provide an important snapshot of the types of occupations that are filled with H-1B workers. From 2010–2015, "Computer and Information Research Scientists" (17.9%) was the most common occupation in the LCA data (Table B-2) followed closely by "Software Developers, Applications, and Systems Software" (17.1%) and "Computer Programmers" (13.9%).

I construct an instrument of the number of immigrants $\widehat{M}_{mx}$ with major m that entered the U.S. labor market alongside the native-born cohort with experience x by interacting the annual cap of H-1B visas allotted in the year cohort x entered the labor market with a proxy for the share of H-1B visas that were allotted to major m. Specifically,

$$\widehat{M}_{mx} = \text{H-1B Cap}_x * \widehat{\text{Share}}_m^{\text{H-1B}}. \tag{3}$$

[6] Signed into law on December 8, 2004, the H-1B Visa Reform Act of 2004 added an additional 20,000 visa slots for individuals receiving a "master's or higher degree from a United States institution of higher education." Companies could begin applying for these additional visa slots on March 8, 2005, the effective date of the law. Fiscal year 2006 was the first year to include the additional slots during the normal application cycle.

The college major of H-1B applicants is not observable and must be indirectly estimated. Using 2010–2015 LCA data, I probabilistically assign all visa applicants to college majors based on their occupations and calculate the share of applicants with each college major.[7] Specifically, I estimate the share of H-1B visas being awarded to college major m as:

$$\widehat{\text{Share}}_m^{\text{H-1B}} = \frac{\sum_{\text{all } k} \text{H-1B Applications}_k * \left(\frac{\text{Population}_{km}}{\text{Population}_k}\right)}{\text{H-1B Applications}}. \tag{4}$$

The summation term in the numerator totals the number of H-1B applicants assigned to major m. An applicant with occupation k is assigned to major m based on the share of workers in the 2010–2012 American Community Survey (ACS) with occupation k that studied major m.[8]

Figure 2 highlights the resulting variation of the instrument. For ease of exposition, I plot the data for seven broad major groups, lagging the H-1B cap by one year to align fiscal years with calendar years. The top panel displays the predicted number of H-1B-capped immigrants, $\widehat{M}_{mx}$, entering the U.S. labor market with major m in a given calendar year. The solid line represents the total H-1B visa cap in October of that year. The lines below represent how the cap is divided across each major. Most of the cap is allotted to STEM and Business majors.[9] Importantly, while changing the timing of the cap (e.g., a cap of 195,000 in 1999 and 115,000 in 2000) wouldn't change the total inflows of H-1B immigrants over time, it would change which major-cohort groups were more affected by the cap increase. The immigrant-native ratio is the variable of interest in Equation 2. The bottom panel displays the instrument used in the analysis, $p_{mx}^{IV} = \widehat{M}_{mx}/N_{mx}$, which is the ratio of the predicted number of H-1B immigrants (top panel) and the number of native workers with the same major that entered the U.S. labor market in the same year. The x-axis of the bottom panel shows the age of the native-born workers when they are observed in 2010 and corresponds to the year of labor market entry seen directly above in the top panel. The solid line represents the average H-1B immigrant-native ratio, weighted by population. STEM majors experience the largest and most variable degree of immigrant competition across cohorts, ranging from about 20

[7] Ideally, one would use a major distribution that is constructed from the period before large changes in the cap. Indeed, the instrument based on immigrant settlement patterns, typically uses geographic distributions from decades before inflows are measured. Detailed occupation data is not available in the LCA data prior to 2010. In robustness analysis, I show that results are similar using the distribution of college majors of Asian immigrants in 1993 using the National Survey of College Graduates.

[8] Occupation k is defined by a six-digit SOC code that has been harmonized across the LCA and ACS. The Population_{km} and Population_k terms include all college graduates aged 24–55. The choice of age group is chosen to straddle two concerns. First, workers may adjust occupation in response to immigration so I try to capture workers earlier in their career before occupation switching becomes too prominent. On the other hand, some occupations such as managerial or executive positions are less common for younger workers so I use a broader age group to more precisely estimate the college major distributions for these occupations.

[9] See Appendix Table B-3 for the major shares of the seven broad major groups used in this figure, as well as the more detailed 40 college majors used in analysis.

to 60 percent of the native population in the skill group.

Despite being nominally temporary, the H-1B visa program affects the long-term stock of immigrants. The H-1B visa is a “dual intent” visa, which means workers can reside in the U.S. with a nonimmigrant status while simultaneously applying for permanent residency. If the employer is willing to sponsor the worker, they can apply for an employment-based immigrant visa (EB-1, EB-2, or EB-3) while on an H-1B visa. This process includes similar wage attestations as the H-1B visa, but takes longer to process. Thus, firms may find it easiest to bring in temporary workers and adjust their status during the H-1B tenure.

Due to country-specific caps that are particularly binding for prominent H-1B source countries, the process of status adjustment can be lengthy. Individuals receive a “priority date” upon applying for an immigrant visa, which signifies their place in line for an available visa. Given their size and importance as sending countries of skilled workers, countries like India and China often have wait times longer than the time allowed on an H-1B visa. To deal with long wait times, AC21 allowed individuals to extend their H-1B visa beyond the maximum six-years if they have a pending or approved immigrant visa application. This change removed the possibility that a nonimmigrant worker would be forced to return to their home country before an available visa could be awarded.

These features – dual intent and visa extensions beyond year six – make it likely that historical changes in the H-1B cap are strongly related to current number of immigrants. Further, the cap changes provide plausibly exogenous variation in the number of immigrants with different college majors that entered the U.S. across different experience cohorts. The next section discusses the data and methodology used to estimate the effect of immigration on the relative wages of high-skilled natives.

3 Methodology

This paper asks whether immigration affects the wages of native workers. To explore this causal relationship, I group individuals into tightly defined skill groups based on their college major and their U.S. labor market experience. The empirical strategy described in this section looks within particular college majors and compares the wages of cohorts that experienced increased immigrant competition relative to those that experienced less competition, controlling for the wage-experience profile common to all college-educated workers. Because immigrants enter and remain in the United States when demand conditions are favorable for their skill group, ordinary least squares is likely biased. I propose an instrumental variables strategy, which takes advantage of changes in the annual cap of H-1B visas that affected both college majors and cohorts differentially.

3.1 Data

3.1.1 Data sources

Data on the U.S. labor market come from the 2010–2012 3-year sample of the American Community Survey (ACS) administered by the U.S. Census Bureau and are dowloaded from the integrated public use microdata samples (IPUMS) at the University of Minnesota Population Center (Ruggles et al., 2015). The ACS provides information on the age, employment, occupation, and earnings of a nationally representative 3% sample of the U.S. population. I identify immigrants using nativity status and observe the year in which they entered the U.S. Importantly, the ACS began asking college graduates their primary and secondary field of study starting with the 2009 survey. These data allow me to construct counts of natives (N_{mx}) and immigrants (M_{mx}) and average log earnings ($\ln w^N_{mx}$) of natives with major m in cohort x.

Administrative data on the H-1B visa program come from the Office of Foreign Labor Certification (OFLC) Disclosure Data and are only used to estimate the share of H-1B visas going to different college majors. The data come from the LCA submitted by firms at application and contain information on the occupation for the potential H-1B visa applicant. Disclosure data are publicly available from the OFLC starting with the 2001 fiscal year. Prior to April 15, 2009, only three-digit occupation codes of the application are available. Since that time, the OFLC data began reporting the six-digit Standard Occupational Classification (SOC) code for the potential job. To take advantage of the richer categorization of occupation and since the change occurred during the 2009 program year, I use data from all subsequent program years, 2010–2015. As described in Section 2.2, the resulting college major distribution is interacted with the H-1B cap defined by federal legislation to estimate the number of H-1B immigrants with major m in cohort x ($\widehat{M}_{mx}$).

Throughout, I draw on other data sources to supplement the main analysis. I use the IPUMS monthly Current Population Survey (Flood et al., 2015) to construct annual major-specific unemployment rates in the U.S. between 1985 and 2013. [10] Historical occupational-wages and immigrant labor supply measures come from the 5% sample of the 1990 U.S. Census downloaded from IPUMS. I also construct various measures of occupation-specific tasks using the O*NET production database (O*NET 21.1, November 2016), which provides measures on the importance of various tasks and abilities at the six-digit SOC code level. To test for robustness of the main results, I use the 1993 National Survey of College Graduates (NSCG) to measure the college majors of immigrants present in the U.S. prior to the expansion of the H-1B cap. Finally, I use data from the 2013-2015 3-year sample of the ACS (Ruggles et al., 2015) when estimating the elasticity of substitution between STEM and non-STEM workers in Section 5.

[10] See Appendix B for details.

3.1.2 Definition of sample, key outcome variables and treatment

Sample—The main analysis sample includes college-educated natives and immigrants divided into skill groups based on their college major and U.S. labor market experience. An individual is considered to be an immigrant if they are a naturalized citizen or not a citizen. Outcomes are averaged over individuals within a skill group. The unit of analysis is a major-experience group.

In the ACS, I observe the primary degree field of all college graduates. I divide workers into 40 college majors, which make up seven broad college major classifications: STEM, Business, Healthcare, Social Sciences, Liberal Arts, Education, and Other. Table B-1 provides the mapping of the primary field of study from the ACS data into the college major groups. I follow Langdon et al. (2011) in grouping STEM fields into five detailed college majors: Computer Science, Math, Engineering, Physical Sciences, and Life Sciences. Of note, I include Computer Engineering graduates in Engineering, Actuarial Science graduates in Finance rather than Math, and students from Health and Medical Preparatory Programs in Pharmacy & Medical Prep. For the remaining fields, I largely follow groupings used by Blom et al. (2015).

I group individuals into single-year experience cohorts, because the empirical approach relies on annual changes in the H-1B cap. Labor market experience is not directly observable. I assume workers already present in the U.S. enter the labor market in the year they turn 22. That year defines the experience cohort of all natives and any immigrant that arrived in the U.S. prior to age 22. I match immigrants aged 22 or older at entry to these experience cohorts based on the year they enter the United States. Given the timing of the H-1B program, I restrict the analysis to the 1990 to 2008 cohorts, which includes natives born between 1968 and 1986. The sample is restricted to individuals of working age, 24-64. While this restriction removes no natives, it does remove immigrants that entered the U.S. between 1990 and 2008 at older ages. The resulting sample is 760 skill group observations across 40 majors and 19 experience cohorts.

Earnings—Following the literature, I construct a wage sample to estimate the average wage of each major-experience group. Because the theory relies on the market wage of a skill group, I restrict the earnings sample to only include individuals whose wage is set by the market, excluding self-employed workers and individuals still in school. I calculate the wage rate paid to a major-experience group from the average log weekly earnings of native workers in that group. I use an individual's wage and salary income over the previous year to measure annual earnings. Weekly earnings is the ratio of annual earnings and imputed weeks worked. I calculate major-experience averages by weighting individuals by the product of their ACS individual weight and annual hours worked. For robustness, I also construct average log weekly earnings using only full-time workers to better approximate the going wage of the group using workers with the most attachment to the labor market.

Employment—I construct two measures of native employment: the employment rate and an index of hours worked over the year. An individual is considered to be employed if they have positive earnings in the previous year. I calculate an individual's annual hours worked by taking the product of weeks worked and the hours worked in a typical week. I then divide this by 2000 hours to create an index to measure full-time equivalency (FTE).

Type of Work—I create measures that describe the position of occupations along the occupation-wage distribution and the skill content of occupations. To measure the position along the wage distribution, I calculate the average log weekly earnings for each occupation in the 1990 U.S. Census and assign an individual their occupation's average.

I measure the skill content of occupations using O*NET data and construct two outcomes. The first outcome compares the importance of interactive tasks relative to quantitative tasks and follows the classification used by Peri and Sparber (2011). Because this measure focuses on communicative rather than supervisory tasks, I create an additional index comparing activities related to leadership and management relative to quantitative tasks. The O*NET activities used in constructing these indices can be found in Table B-5. All of the measures are percentile ranks of the importance of the stated activity or skill in each worker's occupation averaged across the major-experience group then divided to create the ratio.

Treatment—I define the degree of immigrant competition to be the ratio of the number of immigrants to the number of natives in a major-experience group, where counts of immigrants and natives are constructed by summing ACS individual weights within a skill group. This definition most closely matches the theory in which the percent change in the labor supply of a group is measured relative to its initial size. An alternative measure that has been used in the literature (e.g., Borjas, 2003, 2014) is the immigrant share, the ratio of immigrants to the total labor supply of the group (including immigrants). As a robustness check, I use this alternative measure.

3.2 Empirical Strategy

To estimate the effect of immigration on the relative wages of natives, I use the following regression:

$$\ln w_{mx}^{N} = \beta p_{mx} + \mu_m + \chi_x + X_{mx}\Gamma + \epsilon_{mx} \tag{5}$$

where $\ln w_{mx}^{N}$ is the average log weekly earnings of natives with college major m in experience cohort x, μ_m is a set of major fixed effects, which controls for characteristics of a college major common to all cohorts, and χ_x non-parametrically controls for the wage-experience profile of all college-educated workers. Additionally, X_{mx} is a matrix that includes the major-specific unemployment rate at labor market entry estimated in the CPS and major-specific linear cohort trends to control for constant returns to experience that are specific to majors. The key treatment variable p_{mx} measures the relative size of the immigrant shock for the group and is defined as the ratio of immigrants to natives in a group $p_{mx} = M_{mx}/N_{mx}$.

The coefficient of interest, β, measures the relationship between an immigrant induced labor supply shock and the wages of native workers. The empirical strategy identifies a relative wage effect within a major across different cohorts. It does not identify any overall effects of immigration on the wages of natives. The inclusion of major and experience fixed effects removes any effect of immigration that is specific to majors or cohorts. Put differently, the strategy does not identify how the average wages of a particular college major are affected, but it does identify which cohorts were winners and losers around the average effect. Theory suggests that an increase in the relative labor supply of a group should decrease the relative wage, in which case β should be negative.

Identification assumes that, conditional on cohort-invariant major characteristics and controlling for the wage-experience profile of all workers, unobservable differences in average log weekly earnings are uncorrelated with the presence of immigrants. This is a heroic assumption and one that is not likely met. Immigrants choose to arrive and remain in the U.S. when returns to their skills are high. If the positive demand shocks at arrival are correlated with native wages for that cohort in 2010–2012, then OLS estimation will be biased. In particular, group specific demand shocks upon entry into the labor market are likely positively correlated with future labor market earnings. In this case, OLS would bias one away from finding a negative relative wage effect of immigration.

3.2.1 IV Strategy

To remove the positive omitted-variable bias, I implement an IV strategy based on the instrument proposed in Section 2.2. The instrument, p^{IV}_{mx}, leverages national changes in the H-1B visa cap. The key insight is that H-1B visas are predominately awarded to workers in certain fields. Identifying variation across cohorts and majors is summarized in Figure 2.

The IV approach involves estimating a two-stage model where the first-stage is given by

$$p_{mx} = \theta p^{IV}_{mx} + \mu_m + \chi_x + X_{mx}\Gamma + u_{mx} \tag{6}$$

and the second-stage is given by Equation 5. Identification of the second stage requires a strong correlation between the predicted H-1B immigrant-native ratio, p^{IV}_{mx}, and the actual immigrant-native, p_{mx}. Figure 3 plots the first-stage relationship between these variables, net of major and cohort fixed effects. The dashed line in this figure represents the forty-five degree line. The solid line documents the significant positive relationship between p^{IV}_{mx} and p_{mx}. Results from various first-stage specifications are presented in Table 3. The base specification (col. 1) begins by controlling for major and cohort fixed effects. A 10 percentage point increase in the predicted H-1B immigrant-native ratio is associated with a 6.69 percentage point increase in the actual immigrant-native ratio in 2010 (F-stat=23.99). Column 2 controls for the major-specific unemployment rate during the year the cohort entered the U.S. labor market, which only slightly changes the estimate. Finally, column 3 adds major-specific linear cohort trends and the first-stage coefficient decreases in magnitude but remains significant at the 1 percent level (F-stat=17.05).[11] When presenting the earnings results, I present all three specifications. For other outcomes, I only present results using the specification in column 3.

In the presence of heterogenous treatment effects, the 2SLS estimator for β identifies the local average treatment effect (LATE), rather than the average treatment effect (ATE). To the extent that effects differ across immigrant entry mechanisms, my approach isolates the effect of immigration that occurs from changing the H-1B policy. This localized effect is policy relevant. The H-1B program is on the forefront of the policy debate and the findings in this paper inform how changing the cap could alter the distribution of wages among the highly educated.

3.2.2 Estimation Issues

The exclusion restriction relies on two assumptions: (1) the predicted H-1B immigrant shock, conditional on the set of controls, is as good as randomly assigned to each major-experience cell and (2) the only way in which the instrument affects the earnings of natives is through the immigrant shock. These are not testable assumptions, but there is reason to think they are met. The identification strategy is similar in spirit to a continuous difference-in-differences estimator. The reduced-form estimates compare the difference in average log earnings of college majors that receive many H-1B immigrants relative to majors that receive few H-1B immigrants across cohorts graduating in years when the cap was high relative to when the cap was log. Rather than relying on the endogenous decision of immigrant arrival at the national level, this approach takes advantage of changes in a national-level policy and recognizes that college majors are differentially affected. Importantly, the college major distribution used to construct the instrument is held fixed so as not to be responsive to major-specific demand shocks that change over time.

The main threat to identification comes from any wage shocks that are correlated with the timing of H-1B policy and its allocation across majors. Experience fixed effects control for any national policy or wage shock that affects all workers within an experience cohort, including the main effect of the H-1B cap. Major fixed effects control for differences in the wage structure common to all workers within a major. I allow for differential returns to experience across college major by controlling for any major-specific linear trends that may bias estimation. Additionally, major-specific unemployment rates control for major-specific labor market conditions that are contemporaneous with the timing of the cap used to construct the instrument.

Fortunately, many omitted variables stories bias estimation away from finding a negative effect. If immigrants are allowed to enter the U.S. during years in which there is high demand for the

[11] The Stock and Yogo (2005) critical value for 10% maximal IV size is 16.38.

skills they possess, then the estimate will be biased away from a negative effect. Specifically, this relationship removes the concern that negative findings are driven by the U.S. government setting the cap high in response to pressure from the Information Technology sector. The remaining concern is any positive (negative) major-experience wage shock that is not controlled for by the major-specific unemployment rate and is negatively (positively) correlated with the instrument.

A potential concern, that is highlighted in Figure 2, is that increases in the cap are positively correlated with the tech-bubble in the late 1990s and early 2000s. The economy experienced a downturn during a period in which the H-1B visa cap was higher than average. To the extent that the recession during this time particularly affected STEM workers, the IV estimates could be negatively biased. Controlling for the unemployment rate of a group's major during the year they entered the U.S. labor market suggests this is not particularly concerning. As expected, Table 3 shows a significant negative correlation between the major-specific unemployment rate and the relative number of immigrants entering the U.S. Immigrants are less likely to arrive during adverse labor market conditions. Additionally, column 4 of Table 3 shows the relationship between the major-specific unemployment rate at arrival and the instrument. It is encouraging that the effect of this control on the instrument is insignificant. Finally, the results are robust to controlling further for a major's unemployment rate in the five years leading up to and the five years since labor market entry.

An additional estimation issue is the presence of measurement error in two key variables: the college major share, $\widehat{Share}_m^{\text{H-1B}}$ and the sorting of immigrants across experience groups, M_{mx}. To be a threat to identification, this measurement error would need to be correlated with the main error term. If the measurement error is uncorrelated with the main error term, the point estimates would be attenuated and understate the negative effect of immigration. In the analysis, I check the robustness by using alternative measures for each of these variables. First, the college major distribution used to make the instrument is approximated using a mapping between occupations of H-1B applicants and the occupation-major distribution of ACS respondents. Furthermore, the variable is measured using post-treatment data, which could have changed in response to the H-1B program. I implement an alternative measure of the share of college majors studied by immigrants using the 1993 NSCG. Results are robust. Second, experience is imputed. In the main analysis, I group immigrants in experience cohorts based on their year of arrival. This choice implicitly assumes that foreign labor market experience is non-transferrable and has the potential to assign immigrants to an incorrect experience group. Figure A-1 documents the distribution of arrival age for immigrants. Many immigrants arrive in the U.S. at age 22 or younger. These immigrants would be grouped by their age, rather than their year of arrival. To test the robustness of this choice, I also sort immigrants based solely on their age, which groups immigrants arriving later in life with same-aged natives rather than recent college graduates. Again, the main results are robust to this change.

One remaining issue is the presence of heteroskedasticity. The dependent variables are major-experience cell averages. Cells that contain more individual observations are more precisely estimated. To correct for heteroskedasticity, I weight by the number of native observations in the cell. In sensitivity analysis, I show that results are robust to estimates without weights and to alternative weights that more explicitly capture differences in cell-level variance. Indeed, estimates become more precise with weights confirming the need to correct for heteroskedasticity (Solon et al., 2015). Finally, all results report heteroskedasticity-robust standard errors rather than clustered standard errors because the unit of observation is at the same level as "treatment" assignment and neither major or cohort clusters are sampled from the population (Abadie et al., 2017).

4 Results

4.1 Earnings

While the effect of immigration is the focus of estimation, I first present the direct effect of changes in H-1B visa policy on the earnings of U.S.-born workers. Table 4 reports reduced-form estimates of the effect of H-1B visa policy on weekly earnings. The estimate in column 1, which controls for major and cohort fixed effects, suggests a 10 percent increase in the labor supply of a skill group from H-1B visas decreases the relative wages of the group by 0.43 percent. This estimate is not sensitive to controlling for major-specific unemployment rates (column 2). Controlling for major-specific linear cohort trends increases the magnitude to -0.0524 and is statistically significant at the 5 percent level (column 3). As discussed in Section 2.2, Computer Science majors were most affected by the policy. Increases in the H-1B quota meant that visa-driven increases in labor supply of these cohorts increased from about 45 percent to 110 percent. (see Table B-4). This suggests a decrease in relative wages of 3.4 percent for cohorts of computer scientists graduating in the early 2000s (0.0524 x 0.65).

Figure 4 demonstrates the IV strategy. The left panel plots the relationship between the actual immigrant shock and average log weekly earnings of native-born workers, net of major and experience fixed effects. The solid line represents the positive relationship estimated from weighted least squares. As previously discussed, one might be concerned this OLS estimate is positively biased. Immigrants choose to enter the United States during improving labor market conditions which are in turn positively correlated with later labor market earnings. The right panel plots the second-stage relationship between the immigrant shock and native earnings. Strikingly, the relationship reverses and reveals a negative impact of immigration on wages. Figure 4 paints a clear picture. The estimated OLS effect is positive, which is contrary to theory, but consistent with a positive bias from endogenous immigrant entry. The instrument removes the bias.

Table 5 presents OLS and IV estimates of the effect of high-skilled immigration on native earnings. The dependent variable is the mean log weekly earnings of natives and the unit of observation is a major-experience cell. To correct for heteroskedasticity in the measurement of average wages, all regressions are weighted by the number of native observations in the ACS.[12] Column 1 presents the estimate from weighted least squares controlling for college major and cohort fixed effects. The estimate is positive (0.0343), but statistically insignificant. Controlling for the major-specific unemployment rate increases the point estimate (column 2) and additionally controlling for major-specific linear cohort trends reduces the coefficient to 0.008 (column 3). Column 4 instruments for the immigrant-native ratio using the H-1B immigrant-native ratio. The point estimate (-0.0648) is negative and statistically significant at the 10 percent level. Column 6 presents results that control for both the unemployment rate and linear trends. This estimate (-0.119) corresponds to the slope in Figure 4 and is significant at the 5 percent level.

Section 3.2 highlights that the estimate should be interpreted as a relative wage effect on workers with the same college major across cohorts. The average immigrant shock across all STEM majors is about 0.6 with a standard deviation of 0.25. This suggests that a one standard deviation increase in the immigrant shock, adding additional immigrants equivalent to 25 percent of the native population in a skill group, decreases relative earnings for STEM majors by about 3 percent. The H-1B program had the largest impact on the supply of Computer Science workers. The immigrant-native ratio for Computer Science majors increased from about 0.35 in the early 1990s to about 0.85 at the peak of the H-1B cap in the late 1990s and early 2000s, decreasing relative wages of the affected cohorts by about 6 percent.

The main empirical strategy groups workers into 40 college majors across 19 one-year experience cohorts. However, workers with similar majors graduating in consecutive years could be highly substitutable with one another. Figure 2 highlights that most of the variation comes from comparing STEM and non-STEM majors across high and low quota years. To explore this variation more directly, Table A-1 pools workers across broader majors (i.e., STEM and non-STEM) and broader cohorts defined by H-1B quota regimes. The specification in column 2 groups workers into six experience cohorts defined by H-1B quota regimes and compares the relative wages of workers graduating into varying cap levels. Similarly, column 3 groups workers into two broad majors, STEM and non-STEM. Finally, column 4 groups workers into six cohorts and two majors. Across each specification, the coefficient of interest remains negative and increases in magnitude when pooling cohorts, which is consistent with using broader, less substitutable, experience groups.

[12] The sample variance of the sample mean is inversely proportional to the number of observations used to construct the mean. Not all native observations are used in the calculation of average log earnings. The Data Appendix discusses which observations are dropped from the data when constructing average log earnings. However, the total number of native observations is used to allow for a consistent weight across different outcomes.

One potential concern for identification is that policy makers endogenously set the H-1B cap in response to labor demand for STEM workers. Because policy makers set the cap high precisely when demand for tech jobs was surging in the late 1990s, this policy endogeneity would mean that the estimates in Table 5 represent lower-bounds of the actual effect. However, some of the peak years of the H-1B cap overlap with post-tech bubble years. While the main specification controls for an imputed measure of major-specific labor demand, this variation may not fully control for the underlying negative labor demand shock to computer science or engineering majors during the tech bubble. Table A-2 deals further with this potential omitted variable bias. The specification in column 1 additionally controls for the major-specific unemployment rates in each of the five years before a cohort entered the labor market and the five years after they entered the labor market. Results remain little changed when more intensely controlling labor market conditions surrounding graduation. To further test for the robustness of the result, I exclude from the analysis cohorts that graduated during the tech bubble (i.e., 2000–2004). To increase statistical precision that is loss from removing the years with the largest variation in the H-1B cap, I supplement the main sample with cohorts that graduated prior to the creation of the H-1B visa category. Column 2 presents results using the main specification and adding in cohorts that entered the labor market between 1985 and 1989.[13] Results remain similar, albeit more negative, when including the preceding cohorts (column 2) and removing tech bubble cohorts (column 3). Finally, the differences in the two policy landscapes that led to the increase and subsequent decrease in the cap allow for an opportunity to estimate the effects separately over these two periods. The final two columns exploit the variation in the cap both from increases from 1990–2002 (column 4) and decreases from 2002–2008 (column 5). While the increase in the cap in the 1990s was likely demand driven, the motivation for the decrease in the cap is less clear. National security concern in the post-9/11 era is a potential explanation for allowing the cap increase to expire in the early 2000s. Conversely, demand for computer science jobs was relatively low in the post-tech bubble era (see Figure B-1). Reassuringly, the estimates from these two periods are qualitatively similar to the main result, although there is a weak first stage when relying only on the 2002–2008 cohorts.

One might also be concerned with the possibility that a rise in offshoring in the U.S. is positively correlated with changes in H-1B visa policy. To the extent that offshoring is both correlated with the timing of changes in the H-1B cap – increasing in the 1990s and decreasing in the early 2000s – and negatively affects the earnings of STEM majors in particular, the estimate could be negatively biased. However, offshoring is not likely to be biasing the results in this context. Figure A-2 shows that the rise of offshoring in the U.S. does not display the same inverted-U relationship as H-1B

[13] During these years, the H-1B visa category did not exist. Because the preceding visa, the H-1, was not a dual intent visa and temporary nonimmigrant workers were expected to maintain a foreign residence and return home, I set the H-1B cap used to make the instrument to 0 for all majors from these cohorts.

cap changes, and has in fact been increasing linearly throughout the 1990s and 2000s. The major-specific linear cohort trends in the main specification control for this variation. However, it could be that, while offshoring has been increasing linearly, its effect on labor market outcomes has changed overtime. In a robustness check, I control directly for services and materials offshoring in Table A-3.[14]. For this exercise, data are limited to observations from 1997 to 2006. A similar pattern emerges, though the estimates are marginally significant with the reduction in sample size.

The identification strategy relies on the set of college majors that are used as a counterfactual for majors most affected by the H-1B program. Table A-4 highlights that the main result is unsurprisingly driven by Computer Science and Engineering majors (columns 2 and 3), which experienced the most variation in policy-driven changes in immigrant competition. Fortunately, the results are not sensitive to the set of non-STEM majors used as a counterfactual (columns 4–9). Additionally, the results are qualitatively similar when comparing only seven broad major categories or just STEM majors, where Physical Science, Math, and Life Sciences become the comparison to Computer Science and Engineering (results not reported).

The results are also robust to different definitions of skill groups and measures of treatment. Table A-5 tests the robustness to changes in key variables. One might be concerned that immigrant experience is defined by year of immigration and not age. Figure A-1 shows that while most immigrants arrive in the U.S. around or before the age of 24, some arrive at older ages. The main definition of an experience group assumes foreign labor market experience is not transferable to the U.S. Results are similar, though larger in magnitude, when grouping immigrants by age rather than year of arrival (column 2). One might also be concerned with the definition of an immigrant. Immigrants who enter the U.S. at age 2 are more similar to natives than an immigrant arriving at age 22. Results are robust to defining an immigrant as a naturalized citizen or non-citizen who arrived at age 16 or later (column 3). One concern with estimating the number of H-1B immigrants is that the college major distribution is measured using post-period data. Using data on the college majors studied by Asian immigrants who arrived in the U.S. after 1980 from the 1993 NSCG , the results remain similar (column 4). The main specification also classifies the field of Computer Engineering as an Engineering major. Results are similar when classifying this field as Computer Science (column 5). Finally, the law changed on December 8, 2004 to exempt the first 20,000 applications from Master's degree holders from U.S. institutions. Firms were allowed to apply for these newly available slots for the 2005 fiscal year on March 8, 2005, just before the next application cycle began. Because this change occurred mid-cycle, the main specification excluded these slots. Results are similar whether they are included in calendar year 2004 (column 6) or calendar year

[14]Data on offshoring come from Crinò (2010), which includes levels of offshoring by industry. These measures are translated into occupational measures by taking a weighted average of industries, where the weight is the wage bill share for an industry of that occupation. The final control is constructed by averaging the occupational measure using the same weighting matrix from constructing the unemployment rate.

2005 (column 7).

Finally, the main result is not sensitive to alternative specifications. In the main analysis, the treatment variable is the immigrant-native ratio in a skill group. Table A-6 shows that results are qualitatively similar when using alternative measures of treatment that are created only from immigrants that arrived at age 40 or earlier (column 2) or by measuring treatment as the share of the immigrant population (column 3) as done in Borjas (2003). Estimates using this measure are similar in magnitude, but are statistically insignificant. The results are also robust to using mean log annual earnings, mean log hourly earnings, and as the dependent variable (columns 4–6). However though similar in magnitude, the effect is not statistically significant for median log weekly earnings. Additionally, results are similar when not using weights or using a weighting scheme designed to more directly address heteroskedasticity (Table A-7).

Earlier work suggests that the effect of high-skilled immigration is heterogenous across subgroups of natives (Orrenius and Zavodny, 2015; Ransom and Winters, Forthcoming). Table A-8 explores the possibility of heterogenous effects by focusing on the average log weekly earnings of specific native subgroups (Panel A). I consider the following subgroups: native men, native women, white natives, and black natives. The effect is strongest and most precisely estimated among native men. The point estimate is -0.169 and is significant at the 5 percent level (column 2). The point estimate for native women and white natives remains negative, but lacks precision for women. Finally, the estimate on black natives is positive and insignificant, but reasonably sized negative values cannot be rejected.[15]

4.2 Possible Pathways

Section 4.1 documents a negative relationship between the size of an immigration shock and the relative wages of native-born workers. This negative relationship could be the result of a few potential mechanisms – labor supply effects on the extensive or intensive margin and changes in the type of work – which are explored in Table 6. I consider five measures for each major-experience group. The first two outcomes, the employment rate of the skill group (column 1) and average hours worked relative to 2000 hours per year (column 2), measure extensive and intensive margin responses. The remaining three outcomes, the average log occupational weekly earnings, relative intensity of interactive and quantitative tasks, and the relative intensity of leadership and quantitative tasks, measure whether workers changed their quality or type of job in response to immigration. For each measure, I present IV results that include major and cohort fixed effects, a control for the major-specific unemployment rate at graduation, and major-specific linear cohort

[15] Two observations are lost when using average log earnings of black natives. There are no observations of black natives with a major in Secondary Education in the 2005 and 2006 cohorts. Additionally, 147 major-cohort cells have fewer than ten observations used to construct average log earnings and labor supply for black natives.

trends.

The estimate in column 1 suggests that the immigrant shock is associated with an increase in the probability of working for all natives. The estimate is 0.079 and is significant at the 1 percent level. A one standard deviation increase in the immigrant shock variable (about 0.25) is associated with a 1.6 percentage point increase in the propensity to work. This effect is large relative to the percent not working (about 11 percent). The estimate on full-time employment for all natives is close to zero and insignificant (column 2). Overall, the first outcome shows some evidence that immigration increased the likelihood of working, with no effect on the overall amount of hours worked. Disemployment effects do not appear to be driving the negative wage effects found in Section 4.1.

Immigration may not only affect whether or not an individual works, but it may also affect the type of work they do. In response to immigration, natives may leave occupations where immigrants have a comparative advantage. I next explore how immigration affected the occupations of natives in columns 3 through 5 of Table 6. To measure occupational earnings, I assign natives the average log weekly earnings of their occupation from 1990. Column 3 shows that about three-quarters of the wage effect comes from natives working in lower paying occupations. While occupations group workers by specific job categories, I also explore whether the underlying tasks that natives complete are affected by immigration in columns 4 and 5 of Table 6. Each column represents a different comparison. It could be that native-born workers have a comparative advantage in language tasks that make them more able to complete communicative or managerial tasks. Column 4 uses the task classification from Peri and Sparber (2011) that compares the relative importance of interactive tasks to quantitative tasks. I also construct a leadership task index using supervisory activities and compare the relative importance of leadership and quantitative tasks in column 5. I find evidence that immigration causes U.S.-born workers to shift toward more interactive or leadership tasks, relative to quantitative tasks. Both point estimates are positive and significant. These results are consistent with Peri and Sparber (2011) who find that immigrant specialization in quantitative or analytical occupations pushes natives into occupations requiring more interactive tasks.

This section presents evidence on the labor market effects of high-skilled immigration. Workers experiencing relatively large immigrant shocks have lower relative wages, are slightly more likely to be employed, and are more likely to work in occupations where interactive or leadership tasks are important relative to quantitative tasks. The identification strategy allows for clean estimation of these within-major comparisons. However, the question of how high-skilled immigration more broadly affects an entire major group remains. Because data availability limits the ability to empirically address this question, the next section turns to a structural approach to estimate the relative wage effects between STEM and non-STEM workers more broadly.

5 Change in STEM Wage Premium

This section estimates how immigration over the period 1990–2010 has altered the STEM wage premium. This type of exercise is not new in the literature. Earlier work has used the structure of a nested CES model to estimate wage effects across broad education and experience groups (Borjas, 2003; Peri, 2012). Peri et al. (2015) look more closely STEM and simulate the effect of immigration on total factor productivity and skill-biased productivity. In what follows, I simulate the effect of immigration on wage inequality across STEM and non-STEM college majors. While Peri et al. (2015) separate out STEM and non-STEM workers, their analysis closes off the wage inequality channel by assuming these two type of workers are perfectly substitutable with one another.

A simplifying feature of the nested CES framework is the reduction in the number of parameters needed to simulate the relative wage effects of a generalized immigration shock. Suppose there are only two distinct majors, STEM and non-STEM. Changes in relative wages between STEM and non-STEM workers due to a generalized immigration shock is

$$d \ln w_{\text{STEM}} - d \ln w_{\text{non-STEM}} = -\frac{1}{\sigma_M} \left(m_{\text{STEM}} - m_{\text{non-STEM}} \right), \tag{7}$$

where σ_M is the elasticity of substitution between STEM and non-STEM workers. According to this relationship, the relative wage of the major with the larger immigrant shock will decrease. The magnitude of this change depends on the relative size of the supply shocks and the degree of substitutability between the two groups. If STEM and non-STEM workers are less substitutable (smaller σ_M), then the relative wage effect will be larger.

Using the relationship in Equation 7, I consider how the wages of STEM workers have changed relative to non-STEM workers due to the immigration shock experienced between 1990 and 2010. This approach requires two objects, an estimate of the elasticity of substitution between STEM and non-STEM workers (σ_M) and the difference in their relative immigrant supply shocks ($m_{\text{STEM}} - m_{\text{non-STEM}}$). To my knowledge, this elasticity has not been previously estimated in the literature. I estimate this parameter using a state panel of relative wages and relative labor supplies of STEM and non-STEM workers. There are potential concerns with this approach. The location of workers within a state-year-major cell is likely endogenous. Immigrants choose to locate to states where the return to their skills are higher in that year. Additionally, natives may choose to relocate in response to immigrants or wage offers in other locations. Because of the potential for bias, I rely on theory to provide lower and upper bounds of the parameter. Importantly, I find estimates of σ_M that fall within the interval provided by theory and also present bounded estimates of the magnitudes of the relative wage effects, which represent best-case and worst-case scenarios.

The ordering of the CES nests provides a lower and upper bound for the elasticity of substitution between STEM and non-STEM workers. The purpose of the model is to divide workers into groups that become more substitutable at lower nesting levels. In the present setting, this suggests that low- and high-skilled workers are less substitutable than STEM and non-STEM degrees. Further, workers with the same degree (e.g., STEM), but different levels of experience are even more substitutable. Thus, the elasticity of substitution between STEM and non-STEM graduates should fall between the elasticities of substitution of workers with different education levels (σ_E) and different experience levels (σ_X).

There are estimates of σ_E and σ_X in the literature. Borjas (2014) uses a value of 5 for σ_E, whereas Ottaviano and Peri (2012) rely on an estimate of 3.33 when comparing low-skill to high-skilled workers. Sparber (2018) notes that other estimates in the literature range from 1.31 to 2. When simulating wages, Borjas (2014) relies on a value of 6.7 for σ_X and Ottaviano and Peri (2012) estimate it to be between 5.5 and 6.25. The results from Section 4 suggest a slightly higher elasticity. Under the structure of the model described in Appendix C, the point estimate from Table 5 suggests $\sigma_X = 8.4$ (1/0.119). This estimate is likely higher than those found in the literature because workers are grouped into single-year cohorts, rather than five-year experience groups, which would lend toward more substitutability across experience groups. Given the state of the literature, I use 2 and 6.7 as my lower- and upper-bound values for σ_M.

I estimate σ_M by comparing log relative wages to log relative hours worked by STEM and non-STEM majors across 51 states (incl. D.C.) and two time periods using data from the 2010-2012 and 2013-2015 ACS. Table 7 provides estimates from this approach. All specifications include state and period fixed effects and weight observations using the number of ACS observations in a state-period cell or a weight designed to correct for heteroskedasticity.[16] For columns 1 and 2, I measure the labor inputs using log relative hours worked by STEM and non-STEM graduates. However, the CES framework suggests that the appropriate measure of relative labor supply is the relative efficiency units supplied by each input, which requires estimates of the relative productivity of each experience group.[17] To estimate these, I use data across the 1960-2000 censuses and the 2010 3-year ACS (Borjas, 2014). I then aggregate hours worked across different experience groups using a CES function, the estimated productivity parameters, and a value of 6.7 for the elasticity of substitution across experience groups. Columns 3 and 4 present estimates using relative efficiency units.

The estimated value of σ_M depends on which sample is used to construct relative wages. Panel A presents results using a sample of all workers' wages. The estimates range between 4.57 and 5.35 and do not vary substantially with the measure of labor supply or the weighting scheme. The estimates using the wages of full-time workers suggest less substitutability between STEM and non-STEM workers, ranging from 3.22 to 3.66. Importantly, all estimates fall within the range

[16] The appropriate sampling weight for an observation in state s and period t takes the form $\omega_{st} = \left[\frac{\sigma^2_{w,\text{STEM}st}}{N^{\text{STEM}}_{st}} + \frac{\sigma^2_{w,\text{non-STEM}st}}{N^{\text{non-STEM}}_{st}}\right]$, where σ^2 is the variance in log wages for each skill group in a state-year cell and N is the number of observations used to calculate the mean.

[17] See Equation C-4.

prescribed by theory. In the subsequent analysis, I provide simulation results using the lower bound (2), the upper bound (6.7), and estimates from all workers (5) and full-time workers (3.5).

The remaining step is to estimate the STEM and non-STEM immigrant shocks from 1990-2010. An individual's college major is not observable in the 1990 census. So, the stock of STEM and non-STEM graduates in 1990 must be imputed. I use two approaches. First, I probabilistically assign workers in the 1990 census into STEM or non-STEM majors based on their occupation.[18] Then, I group STEM and non-STEM workers into five-year experience bins ranging from 1 to 40 years. I calculate average immigrant shocks by taking log differences in the immigrant stock for each skill-experience group and weighting the change by the income share of immigrants. Shocks at the experience nest translate into STEM and non-STEM shocks by taking a weighted average across experience groups, where the weight is the share of income of the experience group relative to the entire skill group calculated in 2010. The second approach groups workers based on their occupation, where a STEM occupation is defined similarly to Hanson and Slaughter (2016). If workers adjust their occupation in response to immigration, the wage effects based on this supply shock will be dampened.

I find that the relative wages of STEM graduates fell between 1990 and 2010 because immigration increased the relative size of the STEM workforce. Table 8 summarizes this result. Each row uses a different estimate for σ_M, going from less substitutable to more substitutable. Column 1 presents results where workers are grouped by college major. The decrease in relative wages varies from 12 percent, when STEM and non-STEM workers are not very substitutable, to 4 percent, when they are assumed to be as substitutable as workers with the same major but different levels of experience. The final column presents estimates using STEM occupation to categorize workers. Relative wage effects range between 2 percent and 7 percent based on the degree of substitutability. The estimates are large, but consistent with other findings. For instance, Bound et al. (2017) find that "wages for U.S. computer scientists would have been 2.6% to 5.1%" higher in the absence of immigration between 1994 to 2001.

6 Discussion

This paper explores the effect of immigration on the relative wages of college-educated natives. To address this question, I adapt a standard labor demand model to inform an analysis within and across college majors. I find that the wages of workers in cohorts that experienced large immigrant shocks fell relative to workers with the same college major that experienced smaller shocks. Importantly, a novel instrument relying on changes in national H-1B visa policy reveals this

[18] Here, I rely on a procedure similar to the one used to construct the H-1B instrument. Although, I use the 2010 IPUMS harmonized occupation code to allow for merging between 1990 census and 2010-2012 ACS.

negative relationship. I show that the negative relationship is not occurring through disemployment effects, rather natives are seen to be switching to lower paying occupations that require more communicative and supervisory tasks. While consistent with findings in earlier work (Peri and Sparber, 2009, 2011), this paper is the first to document occupation-switching within tightly defined sets of college majors.

More broadly, I show immigration over the past two decades has decreased the wages of STEM graduates by 4 to 12 percent relative to non-STEM workers. This result has important policy implications, but must be interpreted with care. While this paper identifies a negative relative wage effect for those most intensely competing with immigrants for jobs, it is not able to estimate the magnitude of the overall wage effect of immigration. The comparison used in the empirical analysis controls for the overall level effect of immigration on wages and there is strong evidence that suggests it is positive. Local labor markets receiving more immigrants experiences larger increases in average wages of college-educated natives (Peri et al., 2015). Immigrants have positive effects on innovation and productivity in the IT sector specficially (Bound et al., 2017; Khanna and Morales, 2017), and cities and states more generally (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Peri, 2012). Immigration could also have a crowding-in effect at the firm level (Kerr et al., 2015), although there is mixed evidence (Doran et al., 2016). While these seemingly large, positive productivity effects mean that the average college-educated worker stands to gain from skilled immigration, this paper highlights that the subset of workers who most directly compete with immigrants could experience declining relative wages amidst rising absolute wages.

The distributional effects highlighted in this paper are policy relevant and have the potential to affect human capital investment decisions. Recent evidence suggests that college major choice is responsive to labor market conditions (Blom et al., 2015). To the extent that students respond to falling relative wages, the marginal student may switch from STEM to non-STEM fields of study. The implication is that cohorts graduating into a labor market with increased foreign competition for STEM work may select other majors. Current evidence on this question is mixed (Orrenius and Zavodny, 2015; Ransom and Winters, Forthcoming; Anelli et al., 2017) and more work is needed. Policies to increase native STEM degree completion could be even more important in maintaining a pipeline of STEM workers in the presence of immigration.

Finally, the approach used in this paper, grouping workers by college major, has applications in other strands of the immigration literature. For example, Hanson and Slaughter (2016) consider whether STEM immigrants assimilate faster than non-STEM immigrants. However, the occupational switching documented in this paper could complicate the analysis. In this literature, it is common to compare the immigrant-native wage gap for different cohorts of workers across multiple survey waves to see how the wage gap evolves for a cohort over time. Conditioning on a time-variant characteristic, such as occupation, could bias the comparison as cohort composition changes over time. Grouping workers by college major overcomes this challenge.

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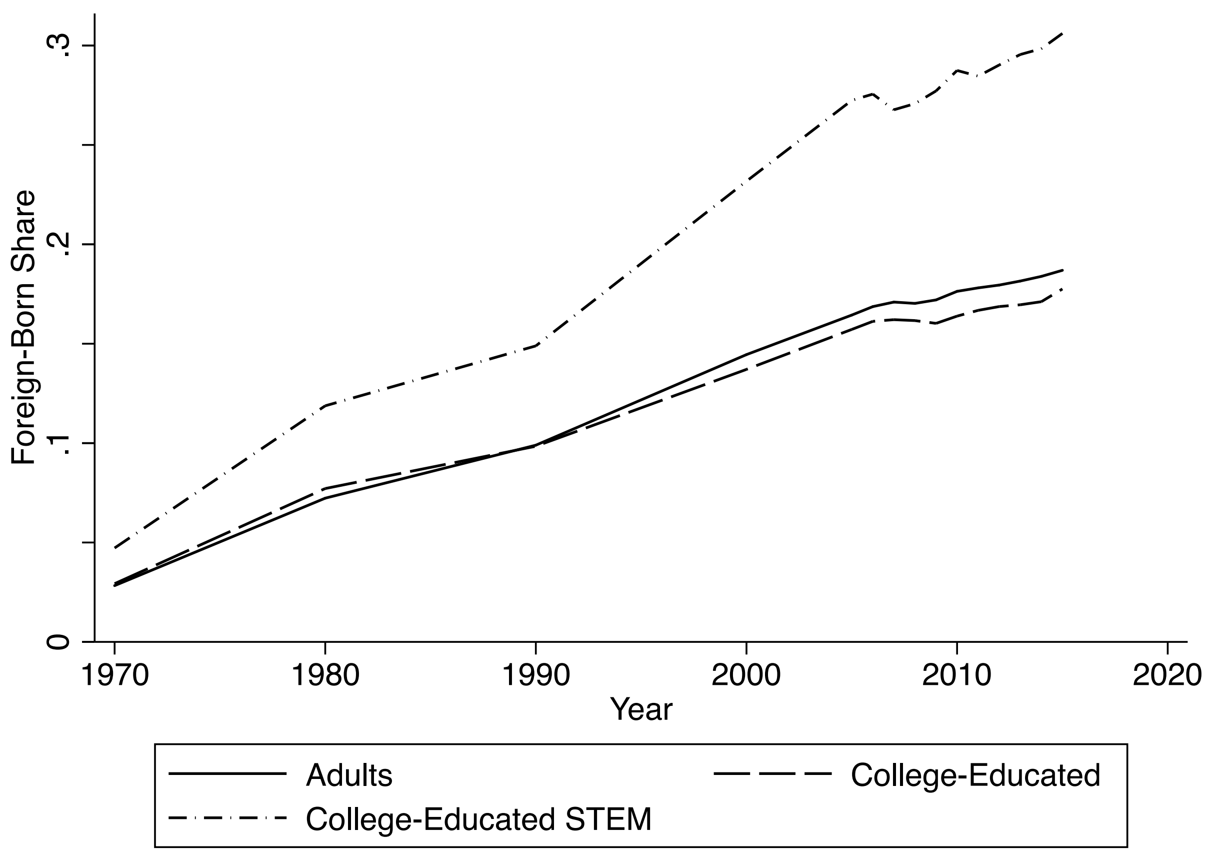
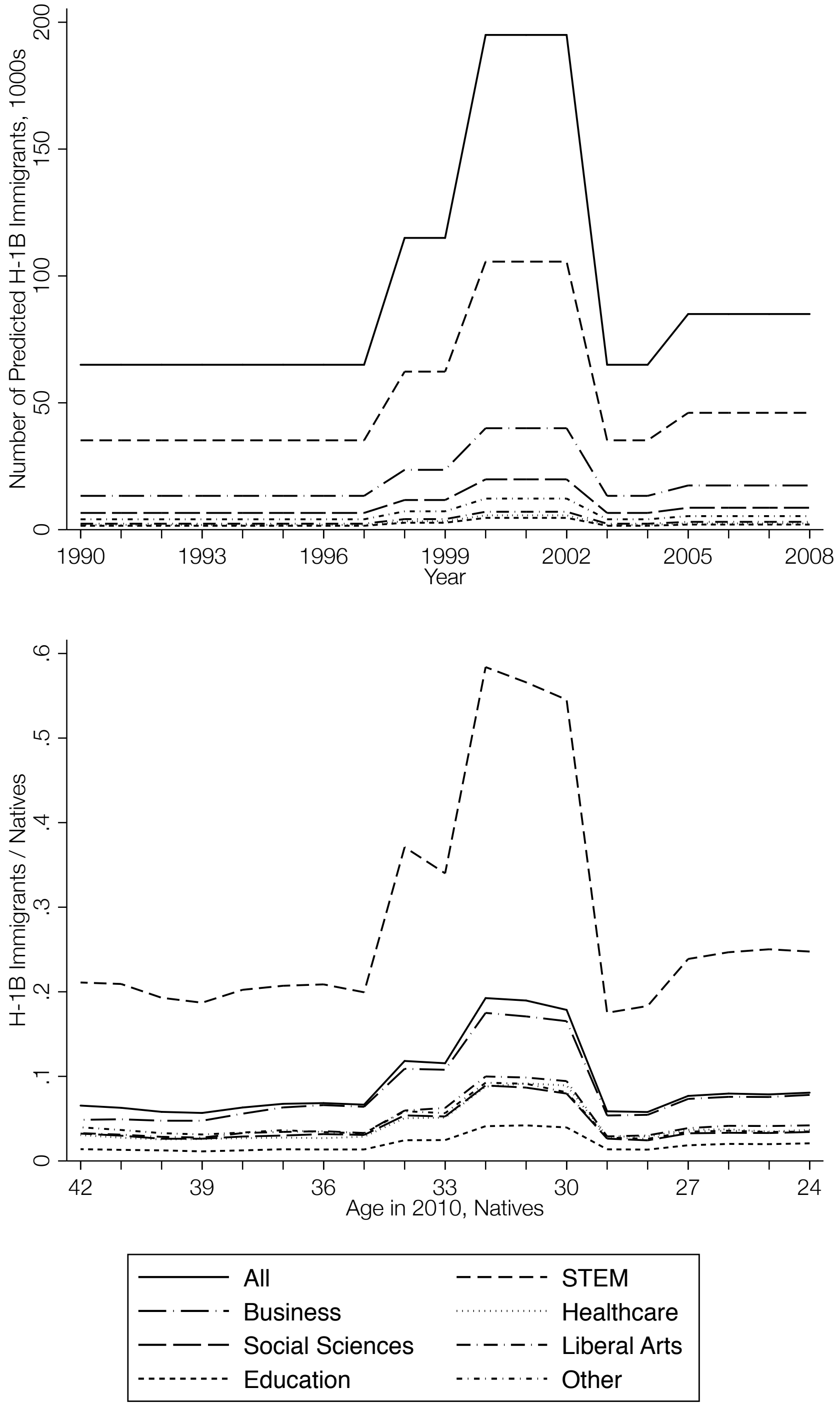
Figure 1: Share of Foreign-Born Adults, 1960-2015



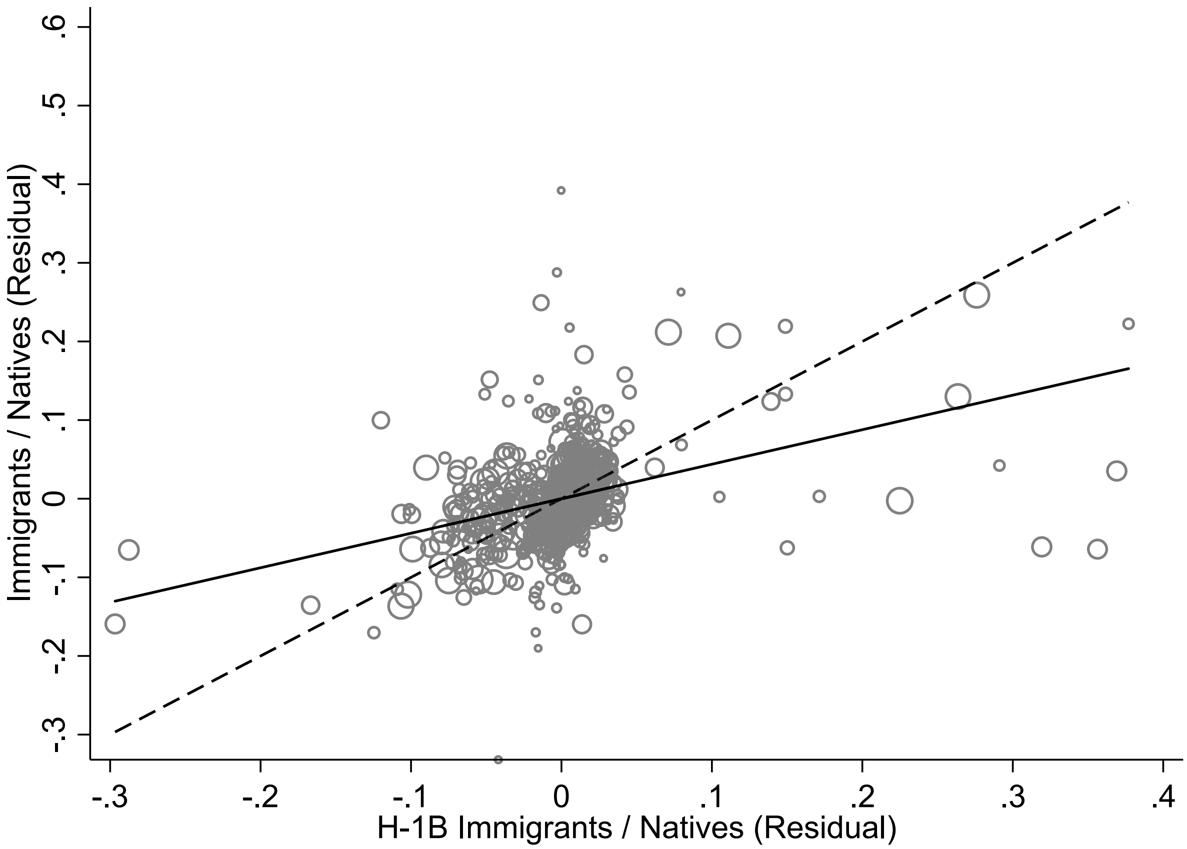
Notes: Based on author's calculations using the 1960-2000 decennial U.S. Census and the 2005-2015 American Community Surveys. The sample includes all individuals aged 24-64 not living in group quarters. Each series plots the share of adults from the given population (all adults, college-educated adults, and college-educated adults in a STEM occupation) that are foreign born. Individuals are considered to be foreign-born in 1960 if they were born outside of the United States and were not a U.S. citizen at birth and in 1970-2010 if they are either a naturalized citizen or not a citizen.

Figure 2: Labor Supply Changes from H-1B Immigration, 1990-2008



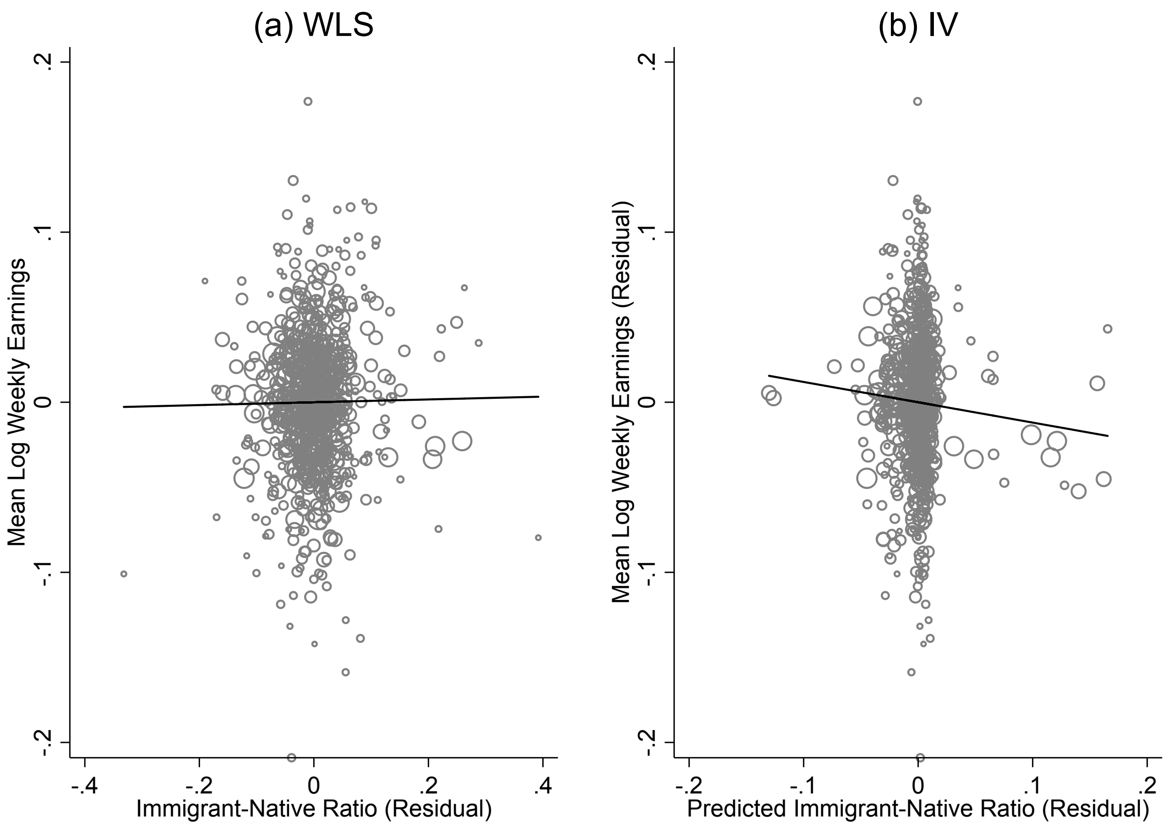
Notes: Based on author's calculations using the 2010-2012 American Community Survey (ACS) and the 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. The top panel plots the predicted number of cap-bound immigrants that entered the U.S. each year due to the H-1B visa program. The H-1B cap is lagged by one year to align USCIS fiscal years with calendar years. The solid line plots the program cap in October of each calendar year. The remaining remaining lines plot the number of immigrants by college major based on the distribution of occupations in the OFLC and the joint distribution of majors and occupations in the ACS. The bottom panel plots the number of H-1B immigrants relative to the number of native-born workers within the corresponding age cohort, where the number of H-1B immigrants in a major-cohort are calculated using the cap in the year the cohort entered the U.S. labor market and the share of H-1B visas going to the major. See Table B-1 for the categorization of ACS degrees and Table B-3 for estimated shares.

Figure 3: Predicting the 2010 Immigrant-Native Ratio with 1990-2008 H-1B Visa Policy



Notes: Based on author's calculations using the 2010-2012 American Community Survey (ACS) and the 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. Each point represent a major-age cohort group. The figures plot residuals from a regression that includes major and cohort fixed effects, a control for the major-specific unemployment rate, and a major-specific linear cohort trend. The vertical axis plots the H-1B immigrant-native ratio, where the number of H-1B immigrants in a major-cohort are calculated using the cap in the year the cohort entered the U.S. labor market and the share of H-1B visas going to the major. The horizontal axis plots the immigrant-native ratio. Marker size represents the the number of native observations in a cell, which is used to weight the regressions. The dashed line is the 45-degree line and the solid line is the fitted line from weighted least squares regression.

Figure 4: The Effect of High-Skilled Immigration on Native Earnings: WLS vs. IV



Notes: Based on author's calculations using the 2010-2012 American Community Survey (ACS) and the 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. Each point represents a major-cohort group. The figures plot residuals from a regression that includes major and cohort fixed effects, a control for the major-specific unemployment rate, and a major-specific linear cohort trend. The vertical axis plots mean log weekly earnings. The horizontal axis plots the immigrant-native ratio (M/N) in panel A and the predicted immigrant-native ratio from the first-stage regression in panel B. The solid line is the fitted line from weighted least squares regression, where the marker size represents the the weight.

Table 1: College Majors by Nativity Status

	All		Men		Women	
	Natives	Immigrants	Natives	Immigrants	Natives	Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)
STEM vs. Non-STEM						
STEM	17.6	35.3	26.4	49.7	9.9	21.8
Non-STEM	82.4	64.7	73.6	50.3	90.1	78.2
Conditional on Non-STEM						
Business	28.2	37.1	38.4	45.8	20.8	31.8
Healthcare	8.4	12.9	3.2	7.5	12.1	16.2
Social Sciences	25.0	17.6	24.7	16.5	25.1	18.3
Liberal Arts	8.6	9.3	8.5	8.4	8.6	9.8
Education	16.2	9.9	9.1	5.9	21.4	12.3
Other	13.7	13.2	16.1	15.9	12.0	11.5

Notes: Based on author's calculations using the 2010-2012 American Community Survey. The sample is all college graduates aged 24-64 that are not living in group quarters. College majors are based on the first degree reported by the respondent and are classified into seven broad majors according to Table B-1.

Table 2: Occupational Distributions by Education Group

	(1)
Panel A: Aggregated Top 5 Occupation Shares	
All Workers	0.22
Only College Educated	0.37
Within-Major (Average)	0.49
Panel B: Index of Similarity	
College vs. Non-College Workers	0.45
One Major vs. Other Majors (Average)	0.65
Within-Major Immigrant vs. Native (Average)	0.80

Notes: Based on author's calculations using the 2010-2012 American Community and 3-digit SOC codes that have been cleaned to construct a crosswalk of occupations between the ACS and H-1B program data. The sample includes all adults aged 24-64 not living in group quarters that have a valid occupation code. Workers with a bachelor's degree are grouped into one of forty college majors. Panel A displays the aggregated shares of the five most common occupations within the listed skill group – all workers, workers that have completed a bachelor's degree, and workers with a given college major. For the "within-major" row, the aggregated share is calculated separately for each major and averaged. Panel B reports the index of similarity. The index in each row is calculated comparing college graduates to noncollege graduates, each college major to college graduates not in that major, and natives and immigrants with the same college major, respectively.

Table 3: Predicting the 2010 Immigrant-Native Ratio with 1990-2008 H-1B Visa Policy

	Immigrant-Native Ratio			H-1B Immigrant-Native Ratio
	(1)	(2)	(3)	(4)
H-1B Immigrant-Native Ratio	0.669**	0.642**	0.439**	
	(0.137)	(0.119)	(0.106)	
Unemployment Rate when		-10.54**	-10.12**	-1.516
Entering Labor Market		(1.929)	(1.737)	(2.877)
Major fixed effects	Yes	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes	Yes
Major-specific linear cohort trend	No	No	Yes	Yes
F-statistic	23.99	29.27	17.05	-
Observations	760	760	760	760

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. In columns (1)-(3) the dependent variable is the major-cohort immigrant-native ratio (M/N) calculated from the 2010-2012 ACS. All college-educated individuals are grouped into 40 college majors and 19 cohorts based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they entered after age 22. Column (1) includes major and cohort fixed effects. Column (2) additionally controls for the major-specific unemployment rate upon entry into the U.S. labor market. The unemployment rate is calculated by converting occupation-specific unemployment rates from the 1990-2008 CPS into major-specific rates using IPUMS 2010 harmonized occupation codes and a major-occupation distribution estimated using the 2010-2012 ACS. Column (3) adds major-specific linear cohort trends. In column (4), the dependent variable is the H-1B immigrant-native ratio ($\hat{M}/N$). Heteroskedasticity-robust standard errors are in parentheses. All regressions are weighted by the number of native observations in a major-experience cell. The reported F-statistic is from the test of the null hypothesis that the coefficient on the H-1B immigrant shock is zero.

** Significant at the 1 percent level
* Significant at the 5 percent level
\+ Significant at the 10 percent level

Table 4: The Effect of H-1B Visa Policy on Native Earnings

	(1)	(2)	(3)
H-1B Immigrant-Native Ratio	-0.0434+	-0.0422+	-0.0524*
	(0.0239)	(0.0238)	(0.0228)
Unemployment Rate when		0.463	0.114
Entering Labor Market		(1.212)	(0.716)
Major fixed effects	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes
Major-specific linear cohort trend	No	No	Yes
Observations	760	760	760

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification Disclosure Data for the H-1B Visa Program. The unit of observation is a major-cohort cell. The dependent variable is average log weekly earnings in 2010. All college-educated individuals are grouped into 40 college majors and 19 cohorts based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they arrived after the age of 22. The explanatory variable is the ratio of predicted H-1B immigrants to natives in a major-cohort cell in the 2010-2012 ACS. Unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. All regressions are weighted by the number of native observations in a major-cohort cell. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level
* Significant at the 5 percent level
+ Significant at the 10 percent level

Table 5: The Effect of High-Skilled Immigration on Native Earnings

	WLS	WLS	WLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant-Native Ratio	0.0343	0.0445	0.00827	-0.0648+	-0.0656+	-0.119*
	(0.0297)	(0.0331)	(0.0276)	(0.0374)	(0.0386)	(0.0568)
Unemployment Rate when		1.052	0.282		-0.229	-1.095
Entering Labor Market		(1.330)	(0.758)		(1.263)	(0.960)
Major fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Major-specific linear trend	No	No	Yes	No	No	Yes
F-statistic	-	-	-	23.99	29.27	17.05
Observations	760	760	760	760	760	760

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification Disclosure Data for the H-1B Visa Program. The unit of observation is a major-cohort cell. The dependent variable is average log weekly earnings. All college-educated individuals are grouped into 40 college majors and 19 cohorts based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they arrived after the age of 22. The explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS. Columns (1)-(3) are estimated using weighted least squares. Columns (4)-(6) are estimated using two-stage weighted least squares where the instrument is the ratio of the number of H-1B immigrants (based on the annual H-1B cap and the estimated H-1B major share) and the number of natives in the 2010-2012 ACS. The unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. All regressions are weighted by the number of native observations in a major-cohort cell. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level
* Significant at the 5 percent level
+ Significant at the 10 percent level

Table 6: The Effect of High-Skilled Immigration on Native Employment

	Employment Rate	Avg. Hours Worked (FTE)	Avg. Occup. Log Weekly Earnings	Interactive/ Quantitative Tasks	Leadership/ Quantitative Tasks
	(1)	(2)	(3)	(4)	(5)
Immigrant-Native Ratio	0.0786**	0.00683	-0.0792*	0.0410+	0.0608*
	(0.0287)	(0.0288)	(0.0314)	(0.0236)	(0.0293)
Unemployment Rate when Entering Labor Market	0.853+	-0.530	-1.003+	1.118**	0.645
	(0.457)	(0.497)	(0.556)	(0.396)	(0.433)
F-statistic	17.05	17.05	17.05	17.05	17.05
Observations	760	760	760	760	760

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, the 2010-2015 Office of Foreign Labor Certification Disclosure Data for the H-1B Visa Program, and the O*NET 21.1 database. All college-educated individuals are grouped into 40 college majors and 19 cohorts based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they arrived after the age of 22. The dependent variable in column (1) is the major-cohort employment rate and in column (2) is the average annual hours worked relative to 2,000 hours (full-time equivalent, FTE). In column (3), individuals are assigned the average log weekly earnings of their occupation from the 1990 census using the IPUMS 2010 harmonized occupation code. The dependent variable is the percentile rank of that occupations earnings. The dependent variables in columns (4) and (5) are ratios of the percentile ranks of task-importance for an individual's current occupation. Column (4) compares interactive to quantitative tasks. Column (5) compares leadership to quantitative tasks. The corresponding O*NET tasks can be found in Table B-5. The explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS. The instrument is the ratio of the number of H-1B immigrants (based on the annual H-1B cap and the estimated H-1B major share) and the number of natives in the 2010-2012 ACS. The unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. All specifications are estimated using two-stage weighted least squares, are weighted by the number of natives observations in a cell, and include major fixed effects, cohort fixed effects, and major-specific linear cohort trends. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level
* Significant at the 5 percent level
+ Significant at the 10 percent level

Table 7: Estimates of the Elasticity of Substitution between STEM and Non-STEM Majors

	(1)	(2)	(3)	(4)
Panel A: All Wage Sample				
Log Relative Hours Worked	-0.219*	-0.211*		
	(0.0902)	(0.0901)		
Log Relative Efficiency Units			-0.195+	-0.187+
			(0.0969)	(0.0968)
Estimate of Elasticity of Substitution between STEM and Non-STEM	4.57	4.74	5.13	5.35
Panel B: Full-Time Wage Sample				
Log Relative Hours Worked	-0.311**	-0.306**		
	(0.0864)	(0.0887)		
Log Relative Efficiency Units			-0.277**	-0.273**
			(0.0948)	(0.0970)
Estimate of Elasticity of Substitution between STEM and Non-STEM	3.22	3.27	3.61	3.66
Weight	ACS Obs.	Var. Weight	ACS Obs.	Var. Weight
Observations	102	102	102	102

Notes: Data are from the 2010-2015 American Community Surveys. The sample is all college-educated individuals aged 24-63 not living in group quarters. The unit of observation is a state-period cell, where the ACS is pooled into two time periods across the 2010-2012 and 2013-2015 surveys. Workers are grouped by whether or not they studied a STEM major. The dependent variable is the difference in average log weekly earnings between STEM and non-STEM majors. The explanatory variable is the difference in log labor supply between STEM and non-STEM majors. In columns (1) and (2), total hours worked for all workers in a state-period cell are used. In columns (3) and (4), STEM and non-STEM efficiency units are calculated using an Armington aggregator over eight 5-year experience groups allowing for imperfect substitutability across experience. Relative productivities are estimated by replicating Borjas (2014) and an elasticity of substitution across experience groups of 6.7. The coefficient on the explanatory variable represents the inverse of the elasticity of substitution between STEM and non-STEM majors. The estimated elasticity is reported below the results. Panel A constructs wages using the earnings sample and Panel B uses full-time workers only. All specifications include state fixed effects and period fixed effects. Columns (1) and (3) are weighted by the number of observations in a cell and columns (2) and (4) by the inverse sample variance weight. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level
* Significant at the 5 percent level
+ Significant at the 10 percent level

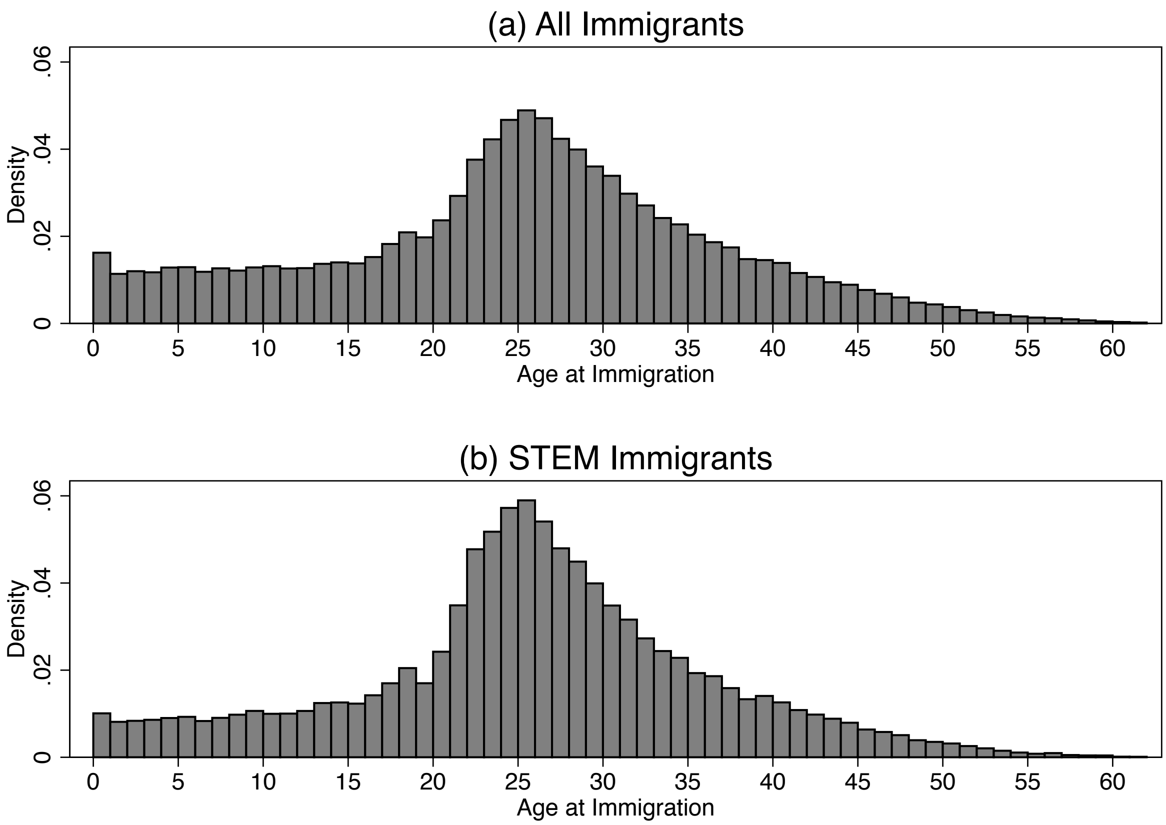
Table 8: Simulated Changes in STEM Wage Premium Due to Immigration, 1990-2010

	College Major (1)	STEM Occupation (2)
m_{STEM}	0.356	0.190
$m_{\text{non-STEM}}$	0.115	0.044
Relative Supply Shift	0.241	0.146
Change in STEM Wage Premium		
Lower Bound: σ = 2	-0.12	-0.07
FT Wage Estimate: σ = 3.5	-0.07	-0.04
All Wage Estimate: σ = 5	-0.05	-0.03
Upper Bound: σ = 6.7	-0.04	-0.02

Notes: Based on author's calculations using the 1990 U.S. decennial census and the 2010-2012 American Community Survey. Income shares are calculated using the 2010-2012 ACS. The immigrant shock in column (1) is calculated based on an individual's college major. An individual's college major in 1990 is imputed based on their IPUMS 2010 harmonized occupation code. The immigrant shock in column (2) is calculated based on an individual's IPUMS 1990 harmonized occupation code. Each row represents a different wage simulation based on different values of the elasticity of substitution between STEM and non-STEM workers. Each value represents the simulated decrease in STEM wages relative to non-STEM wages due to the immigrant shock experienced between 1990 and 2010. See text for specifics on relative wage calculations.

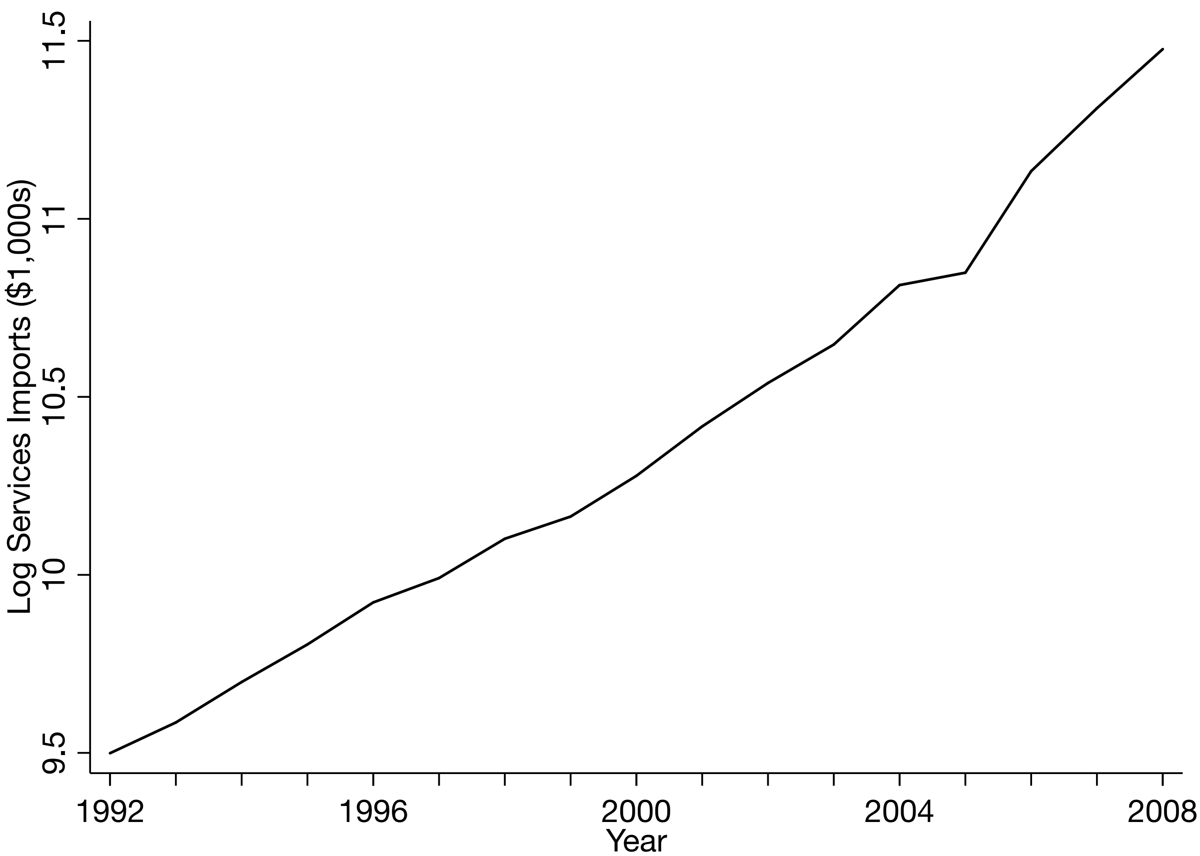
A Appendix

Figure A-1: Distribution of Immigrant Arrival Age



Notes: Based on author's calculations using the 2010-2012 American Community Survey. The sample is all immigrants aged 24-64 not living in group quarters. Immigrant age at arrival is calculated by taking the difference of year of arrival and birth year. Individuals are coded as immigrants if they are a naturalized citizen or not a citizen. Panel (a) is the distribution of age at arrival for all immigrants. Panel (b) restricts the sample to immigrants who studied a STEM field.

Figure A-2: The Growth of Services Offshoring in the United States, 1992–2008



Notes: Based on author's calculations using International Services data in the U.S. Economic Accounts of the Bureau of Economic Analysis. Data are from 1992–2008 and include imports from unaffiliated persons in – financial services; insurance services, telecommunications; computer and information services; management and consulting services; research and development and testing services; operational leasing; accounting, auditing and bookkeeping services; advertising; architectural, engineering and other technical services; installation, maintenance, and repair of equipment; legal services; and other business, professional, and technical services.

Table A-1: The Effect of High-Skilled Immigration on Native Earnings, Robustness Checks

	Baseline (1)	Pool Cohorts by Quota Regime (2)	Pool Majors by STEM & Non-STEM (3)	Pool Majors and Cohorts (4)
Immigrant-Native Ratio	-0.119*	-0.156*	-0.108*	-0.135**
	(0.0568)	(0.0757)	(0.0451)	(0.0154)
Unemployment Rate when Entering Labor Market	-1.095	-2.391	-9.736**	-9.871**
	(0.960)	(1.529)	(1.669)	(0.589)
F-statistic	17.05	6.31	12.60	8.56
No. of Majors	40	40	2	2
No. of Cohorts	19	6	19	6
Observations	760	240	38	12

Notes: Data are from the 2010-2012 American Community Survey, the 1985-2013 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. The dependent variables are major-cohort cell averages of log earnings using weekly earnings. All college-educated individuals are grouped into college majors and cohorts as indicated in the column headings based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they arrived after the age of 22. The explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS which is instrumented by the ratio of the estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. The unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. Column (1) is preferred specification from Table 5. In column (2), individuals are grouped into multi-year cohorts that had the same H-1B quota at graduation: 1990-1993, 1994-1997, 1998-1999, 2000-2002, 2003-2004, and 2005-2008. In column (3), workers are grouped into only two majors, STEM and non-STEM. Column (4) pools workers into the 6 cohorts from column (2) and the 2 majors from column (3). In each, earnings are constructed by averaging over all natives within a major-cohort group. All columns include major fixed effects and experience cohort fixed effects, and major-specific linear experience trends. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level
* Significant at the 5 percent level
+ Significant at the 10 percent level

Table A-2: The Effect of High-Skilled Immigration on Native Earnings, Robustness Checks

	Pre-Entry and Post-Entry Unemployment	Add 1985-1989 Cohorts	Exclude Tech Bubble, 2000-2004	Years 1990-2002	Years 2002-2008
	(1)	(2)	(3)	(4)	(5)
Immigrant-Native Ratio	-0.128*	-0.165*	-0.190*	-0.128**	-0.143
	(0.0624)	(0.0667)	(0.0902)	(0.0368)	(0.303)
Unemployment Rate when Entering Labor Market	-0.0629	-0.318	1.820	0.573	-1.315
	(1.225)	(1.080)	(1.327)	(1.226)	(4.079)
Major fixed effects	Yes	Yes	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Major-specific linear trend	Yes	Yes	Yes	No	No
F-Statistic	20.99	21.99	17.74	53.27	2.03
No. of Majors	40	40	40	40	40
No. of Cohorts	19	24	19	13	7
Observations	760	960	760	520	280

Notes: Data are from the 2010-2012 American Community Survey, the 1985-2013 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. The dependent variables are major-cohort cell averages of log earnings using weekly earnings. All college-educated individuals are grouped into 40 college majors and cohorts based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they arrived after the age of 22. The explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS which is instrumented by the ratio of the estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. The unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. Column (1) controls for the major-specific unemployment rates in the five years before and the five years after labor market entry. Column (2) adds cohorts that entered the labor market from 1985–1989. For these cohorts, the H-1B cap is set to 0 because the H-1 visa during this time was not dual intent. Using these additional years, column (3) removes from analysis cohorts that graduated during the tech bubble, cohort years 2000-2004. Columns (4) and (5) restrict the analysis to experience cohorts from the years listed in the column headers. All columns include major fixed effects and experience cohort fixed effects. Major-specific linear experience trends are only included in columns (1)–(3). Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level

* Significant at the 5 percent level

\+ Significant at the 10 percent level

Table A-3: The Effect of High-Skilled Immigration on Native Earnings, Robustness Checks

	IV (1)	IV (2)	IV (3)	IV (4)
Immigrant-Native Ratio	-0.165	-0.168+	-0.187+	-0.158+
	(0.101)	(0.0991)	(0.112)	(0.0941)
Unemployment Rate when	-1.488	-1.458	-2.400+	-0.999
Entering Labor Market	(1.057)	(0.978)	(1.228)	(1.077)
Services Offshoring when		-0.00691**		-0.00836*
Entering Labor Market		(0.00256)		(0.00360)
Materials Offshoring when			-0.0148	0.00736
Entering Labor Market			(0.00908)	(0.0124)
F-Statistic	7.144	7.173	6.973	7.646
Observations	400	400	400	400

Notes: Data are from the 2010-2012 American Community Survey, the 1997-2006 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. Data on service and materials offshoring by industry-occupation come from Crinò (2010) and are limited to the years 1997-2006. The dependent variable is the major-experience cell average of log weekly earnings. All college-educated individuals are grouped into 40 college majors and 10 cohorts based on entry into the U.S. labor market from 1997-2006. Natives are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on an imputed measure of U.S. labor market experience and matched to the corresponding native cohort. Unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. All columns include major fixed effects, experience cohort fixed effects, and major-specific linear experience trends. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level
* Significant at the 5 percent level
\+ Significant at the 10 percent level

Table A-4: The Effect of High-Skilled Immigration on Native Earnings, Robustness Checks

	Baseline	Drop Comp. Sci.	Drop Engineering	Drop Business	Drop Healthcare	Drop Soc. Sci.	Drop Liberal Arts	Drop Education	Drop Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Immigrant-Native Ratio	-0.119*	-0.0838+	-0.0667	-0.122*	-0.149*	-0.113*	-0.107*	-0.132*	-0.138*
	(0.0568)	(0.0480)	(0.109)	(0.0561)	(0.0597)	(0.0573)	(0.0547)	(0.0620)	(0.0603)
Unemployment Rate when	-1.095	-0.270	0.0751	-1.659	-1.230	-1.161	-1.066	-0.774	-1.849+
Entering Labor Market	(0.960)	(0.859)	(1.255)	(1.025)	(1.117)	(0.983)	(0.937)	(1.117)	(1.037)
F-Statistic	17.05	28.55	7.100	17.74	17.26	16.72	16.94	16.24	16.47
No. of Majors	40	39	39	34	37	32	36	34	32
No. of Cohorts	19	19	19	19	19	19	19	19	19
Observations	760	741	741	646	703	608	684	646	608

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. The dependent variables are major-cohort cell averages of log earnings using weekly earnings. All college-educated individuals are grouped into 40 college majors and 19 cohorts based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they arrived after the age of 22. The explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS which is instrumented by the ratio of the estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. Columns (2)-(9) drop major-experience cells with the major listed in the column header. Column (10) performs the analysis across the seven broad major categories listed in Table B-1 and the unit of observation is a broad major-experience cell. Unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. All columns include major fixed effects, experience cohort fixed effects, and major-specific linear experience trends. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level
* Significant at the 5 percent level
\+ Significant at the 10 percent level

Table A-5: The Effect of High-Skilled Immigration on Native Earnings, Robustness Checks

	Baseline (1)	Cohort by Age of Immigrant (2)	Young Immigrants as Natives (3)	NSCG Major Distribution (4)	Computer Engineering as Comp. Sci. (5)	Master's Exemption in 2004 (6)	Master's Exemption in 2005 (7)
First-Stage Excluded Instrument							
Immigrant-Native Ratio	0.439**	0.188**	0.400**	0.470**	0.455**	0.439**	0.431**
	(0.106)	(0.0414)	(0.119)	(0.0689)	(0.115)	(0.109)	(0.106)
Unemployment Rate when	-10.12**	-2.148+	-9.426**	-10.53**	-4.500**	-10.21**	-10.03**
Entering Labor Market	(1.737)	(1.128)	(1.583)	(1.511)	(0.865)	(1.730)	(1.737)
F-statistic	17.05	20.64	11.25	46.43	15.71	16.25	16.63
Second-Stage							
Immigrant-Native Ratio	-0.119*	-0.279*	-0.121+	-0.0978*	-0.118*	-0.127*	-0.125*
	(0.0568)	(0.122)	(0.0715)	(0.0448)	(0.0564)	(0.0596)	(0.0593)
Unemployment Rate when	-1.095	-0.485	-0.689	-0.862	-0.533	-1.181	-1.156
Entering Labor Market	(0.960)	(0.743)	(1.002)	(0.837)	(0.452)	(0.977)	(0.981)
Observations	760	760	760	760	760	760	760

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, the 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program, and the 1993 National Survey of College Graduates (NSCG). The dependent variable is the major-cohort cell average of log weekly earnings. All college-educated individuals are grouped into 40 college majors and 19 labor market cohorts. Natives are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on an imputed measure of U.S. labor market experience and matched to the corresponding native cohort. Column (1) is the main specification from Column (6) of Table 5. The remaining columns alter the specification in the following ways. Column (2) assigns immigrants to experience cohorts based on their age, rather than year of entry. Column (3) redefines an immigrant to be any naturalized citizen or non-citizen arriving in the U.S. at age 16 or later. Column (4) uses the college major share of Asian immigrants in the NSCG who arrived in the U.S. in 1980 or later. Column (5) classifies the field of computer engineering as a computer science major, rather than engineering. Column (6) adds 20,000 to the H-1B cap in calendar year 2004. Column (7) adds 20,000 to the H-1B cap in calendar year 2005. The explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS, which is instrumented by the ratio of the estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. Unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. All columns include major fixed effects, experience cohort fixed effects, and major-specific linear experience trends. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level

* Significant at the 5 percent level

+ Significant at the 10 percent level

Table A-6: The Effect of High-Skilled Immigration on Native Weekly Earnings, Robustness Checks

	Average Log Weekly Earnings			Average Log Annual	Average Log Hourly	Median Log Weekly
	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant-Native Ratio	-0.119*			-0.127*	-0.128*	-0.0798
	(0.0568)			(0.0600)	(0.0548)	(0.0506)
Under 40 Immigrant-Native Ratio		-0.133*				
		(0.0635)				
Immigrant Share			-0.235			
			(0.154)			
Unemployment Rate when Entering Labor Market	-1.095	-1.184	-0.720	-1.174	-0.696	-1.852*
	(0.960)	(0.999)	(0.908)	(1.032)	(0.926)	(0.920)
F-statistic	17.05	17.53	56.1	17.05	17.05	17.05
Observations	760	760	760	760	760	760

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification Disclosure Data for the H-1B Visa Program. The dependent variable is average log weekly earnings for columns (1)-(3), average log annual earnings for column (4), average log hourly earnings for column (5), and the median log weekly earnings for column (6). All college-educated individuals are grouped into 40 college majors and 19 cohorts based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they arrived after the age of 22. In columns (1) and (4)-(6), the explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS. In column (2), immigrants who entered the U.S. after age 40 are removed from the explanatory variable. In column (3), the explanatory variable is the share of immigrants in the major-cohort cell. All specifications control for college major and cohort fixed effects, the major-specific unemployment rate at labor market entry, and major-specific linear cohort trends. Unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. All regressions are weighted by the number of native observations in a major-cohort cell. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level

* Significant at the 5 percent level

+ Significant at the 10 percent level

Table A-7: The Effect of High-Skilled Immigration on Native Earnings, Alternative Weights

	All Workers		Full-Time Workers	
	Pooled	Men	Pooled	Men
Weights used:	(1)	(2)	(3)	(4)
Unweighted	-0.0647	-0.154	-0.0298	-0.108
	(0.0687)	(0.108)	(0.0629)	(0.0953)
Number of native observations in major-cohort cell	-0.119*	-0.169*	-0.0888+	-0.134*
	(0.0568)	(0.0687)	(0.0518)	(0.0601)
Number of native observations used to average wages	-0.121*	-0.197**	-0.0993+	-0.159**
	(0.0565)	(0.0638)	(0.0520)	(0.0549)
Sample variance of average wages	-0.117*	-0.203**	-0.0988*	-0.169**
	(0.0521)	(0.0586)	(0.0480)	(0.0520)

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. The dependent variables are major-cohort cell averages of log earnings using weekly earnings. All college-educated individuals are grouped into 40 college majors and 19 cohorts based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they arrived after the age of 22. The explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS which is instrumented by the ratio of the estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. Earnings in columns (1) and (3) are constructed by averaging over all natives and in columns (2) and (4) by averaging over the earnings of males. Unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. Each row is weighted by the weight listed in the left column. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level
* Significant at the 5 percent level
+ Significant at the 10 percent level

Table A-8: The Effect of High-Skilled Immigration on Native Earnings by Group

	All	Men	Women	White	Black
	(1)	(2)	(3)	(4)	(5)
Panel A: Average Log Weekly Earmings					
Immigrant-Native Ratio	-0.119*	-0.169*	-0.0897	-0.115*	0.0934
	(0.0568)	(0.0687)	(0.104)	(0.0568)	(0.168)
Unemployment Rate when	-1.095	-0.211	-1.401	-0.946	1.230
Entering Labor Market	(0.960)	(1.267)	(1.562)	(0.945)	(2.732)
Panel B: Employment Rate					
Immigrant-Native Ratio	0.0786**	0.0162	0.0454	0.0960**	0.0584
	(0.0287)	(0.0238)	(0.0469)	(0.0303)	(0.0841)
Unemployment Rate when	0.853+	0.693	0.917	0.955*	1.671
Entering Labor Market	(0.457)	(0.473)	(0.643)	(0.484)	(1.552)
Panel C: Avg. Hours Worked (FTE)					
Immigrant-Native Ratio	0.00683	-0.0781+	-0.0415	0.00951	0.0223
	(0.0288)	(0.0418)	(0.0453)	(0.0310)	(0.0817)
Unemployment Rate when	-0.530	-1.352	-1.247+	-0.311	-0.248
Entering Labor Market	(0.497)	(0.873)	(0.697)	(0.526)	(1.297)
F-statistic	17.05	17.05	17.05	17.05	17.05
Observations	760	760	760	760	758

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 Office of Foreign Labor Certification Disclosure Data for the H-1B Visa Program. The dependent variables are the major-cohort cell average of log weekly earnings in Panel A, the employment rate in Panel B, and average hours worked indexed to full-time equivalency in Panel C. All college-educated individuals are grouped into 40 college majors and 19 cohorts based on entry into the U.S. labor market from 1990-2008. Individuals are grouped by year of birth and are assumed to enter the labor market at age 22. Immigrants are grouped based on year of entry into the United States if they arrived after the age of 22. The explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS. All columns are estimated using two-stage weighted least squares where the instrument is the ratio of the estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. Outcomes are constructed by averaging over natives in the subgroup listed in the column header. Unemployment rate is the major-specific unemployment rate during the year the cohort entered the U.S. labor market. All regressions are weighted by the number of native observations in a major-cohort cell. Heteroskedasticity-robust standard errors are reported in parentheses.

** Significant at the 1 percent level
* Significant at the 5 percent level
+ Significant at the 10 percent level

B Data Appendix

This appendix provides additional details regarding data sources and the construction of the analysis dataset and outcome variables.

Data Sources The data used throughout this paper are publicly available and can be downloaded at the following websites:

ACS: https://usa.ipums.org/
CPS: https://cps.ipums.org/
1993 NSCG: https://ncsesdata.nsf.gov/datadownload/
OFLC Disclosure Data: https://www.foreignlaborcert.doleta.gov/performancedata.cfm
O*NET: http://www.onetcenter.org/dictionary/21.1/excel/
Service Offshoring (Crinò, 2010): https://sites.google.com/site/crinoecon/home/Research

Occupations I construct two crosswalks to have a consistent set of SOC occupation codes across the ACS, OFL, and O*NET data. The file *occsoc_occsoc_cl_crosswalk.dta* merges onto the ACS sample. The file *soc_occsoc_cl_crosswalk.dta* merges onto the OFL and O*NET data. The resulting *occsoc_cl* variable is used across these data sources.

Nativity Status I classify an individual as an immigrant if they are a "naturalized citizen" or "not a citizen".

Experience Cohorts I place workers into experience cohorts that are determined by age and immigrant year of arrival and defined by the year they enter the U.S. labor market. I assume both immigrant and native workers that are present in the U.S. at age 22 enter the labor force at this time. Immigrants entering the U.S. after this age are placed into the experience cohort associated with their most recent year of arrival. For example, the 1992 cohort includes three sets of individuals: (1) natives born in 1970, (2) immigrants born in 1970 that arrived in the U.S. in 1992 or earlier, and (3) immigrants born before 1970 that arrived in the U.S. in 1992.

Earnings and Employment To construct weekly earnings, I divide a person's annual wage and salary income by an imputed measure of weeks worked. The ACS reports weeks worked as an interval. I impute weeks in the following manner: 7 weeks if worked 1–13 weeks, 20 weeks if worked 14–26 weeks, 33 weeks if worked 27–39 weeks, 43.5 weeks if worked 40–47 weeks, 48.5 weeks if worked 48–49 weeks, and 51 weeks if worked 50–52 weeks.

Occupational Tasks O*NET occupational task classifications can be found in Table B-5. The table reports the element and element name used in each task grouping. I use these groupings to construct measures of relative task importance for each occupation by calculating the percentile rank of importance of a given task. The outcome for analysis is the ratio of the average percentile ranks within the major-cohort cell of the two tasks being compared.

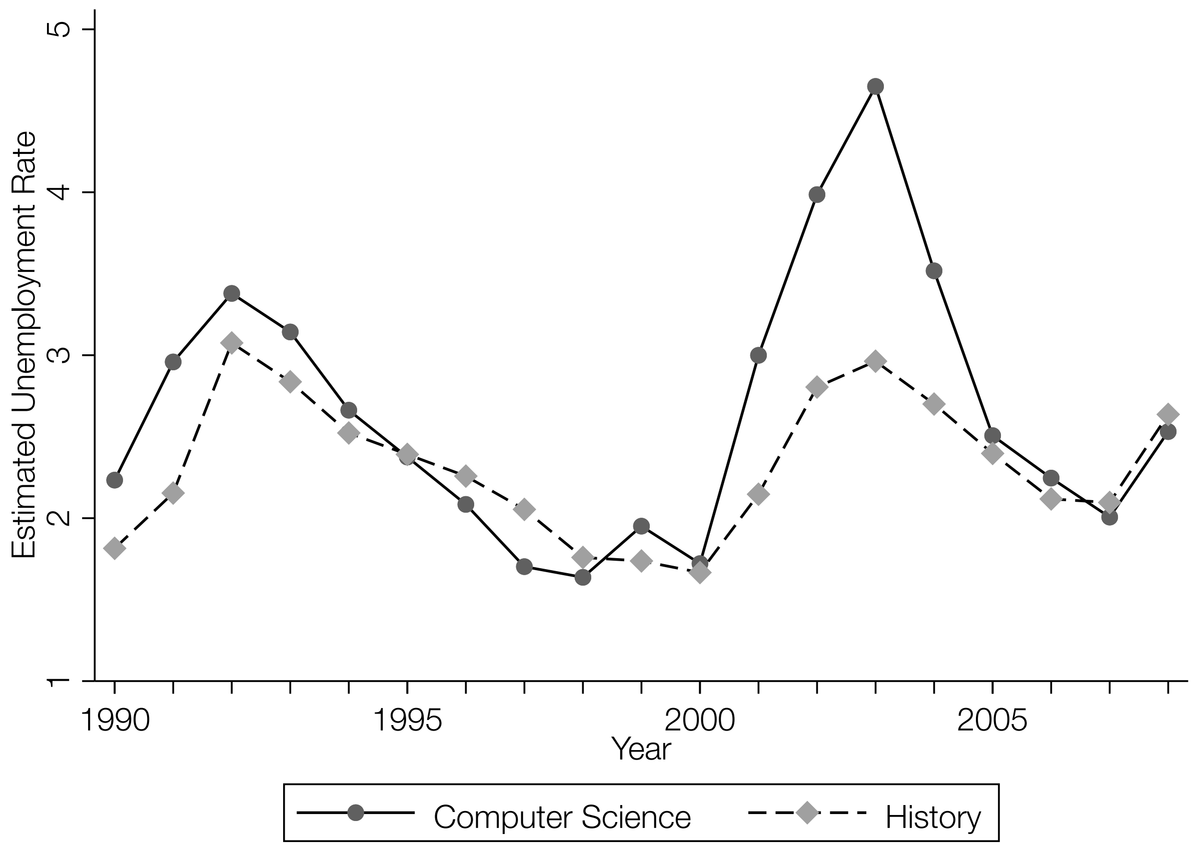
Occupational Earnings I calculate the average log weekly earnings of each occupation using the 1990 5% sample of the U.S. Census from IPUMS. Occupations in the 2010–2012 ACS file are linked using the IPUMS 2010 harmonized occupation code.

Major-specific unemployment rates I construct major-specific unemployment rates in the U.S. between 1985 and 2013 using the occupation-specific unemployment rates calculated from the CPS and the major-occupation distribution estimated in the ACS. The major-specific unemployment rate in a given year is calculated as the average of the occupation-specific rates weighted by the share of individuals in a major with that occupation. Figure B-1 shows the estimated unemployment rates for two majors: Computer Science and History.

Sample Selection I use a number of criterion to select the sample. First, I remove all individuals in group quarters, those not aged between 24 and 64 (inclusive), and anyone that has not graduated college. From the resulting observations, I create three separate samples: (1) a "Occupation sample" to estimate the major-occupation distribution, (2) an "Employment sample" to construct counts of natives and immigrants, as well as average employment outcomes, and (3) an "Earnings sample" used to construct average earnings outcomes at the major-cohort level. Table B-6 reports the additional criterion used to select the three samples. Table B-7 reports summary statistics on the number of observations by nativity status for each college major.

Estimated H-1B Immigrants ($\widehat{M}_{mx}$) Table B-2 highlights the approach used to estimate the number of H-1B immigrants with major m and in cohort x for the three largest H-1B occupations already mentioned. Panel A shows that 21.4 percent of "Computer and Information Research Scientists" studied Computer Science, with Engineering being the second most prominent major at 16 percent. Panels B and C show that "Software Developers, Applications, and Systems Software" and "Computer Programmers" mainly studied Computer Science (35% and 41.7%) and Engineering (33.6% and 18.1%). To calculate the major share, each occupation share is multiplied by the share of the occupation with the major and summed across occupations. Table B-3 reports all estimated major shares.

Figure B-1: Example of Major-Specific Unemployment Rates, Computer Science and History



Notes: Based on author's calculations using the 2010-2012 American Community Survey and the 1990-2008 Current Population Survey.

Table B-1: College Major Classification

Skill Group	College Major	IPUMS Detailed Code
STEM	Computer Science	2100, 2101, 2102, 2105, 2106, 2107
	Math	3700, 3701, 3702, 4005
	Engineering	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2499, 2500, 2501, 2502, 2503, 2504, 2599, 3801, 5008
	Life Sciences	1103, 1104, 1105, 1106, 1301, 3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3611, 3699, 4006
	Physical Sciences	5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007
Business	Accounting	6201
	Economics	1102, 5501
	Finance	6202, 6207
	Marketing	6206
	Business Management	6203
	Other Business	6200, 6204, 6205, 6209, 6210, 6211, 6212, 6299
Healthcare	Pharmacy & Medical Prep	6106, 6108
	Nursing	6107
	Technical Health Fields	4002, 5102, 6100, 6102, 6103, 6104, 6105, 6109, 6199
Social Sciences	Communication	1901, 1902, 1903, 1904, 2001
	Political Science, International Relations, Pre-Law & Legal Studies	3201, 3202, 5505, 5506
	Sociology	5507
	History	6402, 6403
	Pschology	5200, 5201, 5202, 5203, 5205, 5206, 5299
	Public Admin, Public Policy, and Public Helath	5401, 5402, 6110
	Social Work	5403, 5404
	Social Science Fields, Other	1501, 4001, 4007, 5500, 5502, 5503, 5504, 5599
Liberal Arts	Philosophy	4801, 4901
	Liberal Arts and Humanities	3401, 3402
	Languages	2601, 2602, 2603
	Literature	3301, 3302
Education	Early and Elementary Education	2304, 2307
	Secondary Education	2309
	General Education	2300, 2312
	Field Specific Education	2305, 2306, 2308, 2311, 2313, 2314
	Special Needs Education	2310
	Other Education	2301, 2303, 2399, 3501
Other	Agriculture, Forestry, and Natural Resources	1100, 1101, 1199, 1302, 1303
	Architecture	1401
	Family and Consumer Sciences	2901
	Visual and Performing Arts	6000, 6001, 6002, 6003, 6005, 6006, 6007, 6099
	Leisure Studies	4101
	Industrial and Commercial Arts	6004
	Protective Services	5301
	Other Fields	2201, 4000, 5098, 5601, 5701, 5901

Notes: College Majors are grouped into 7 broad classifications: STEM, Business, Healthcare, Social Sciences, Liberal Arts, Education, and Other. The forty detailed major groups are listed in the second column. The corresponding codes for the IPUMS ACS variable `degfieldd` are given in the third column.

Table B-2: Three Largest H-1B Occupations

	(1)
Panel A: Computer and Information Research Scientist (15-1121)	
Share of all H-1B Applications, 2010-2015	17.9%
Share of Occupation in College Major, 2010-2012	
Computer science	21.4%
Engineering	16.0%
Other business	10.1%
Business management	7.8%
Finance	4.5%
All other majors	40.2%
Panel B: Software Developers, Applications, and Systems Software (15-113X)	
Share of all H-1B Applications, 2010-2015	17.1%
Share of Occupation in College Major, 2010-2012	
Computer science	35.0%
Engineering	33.6%
Math	4.5%
Other business	4.4%
Physical sciences	3.3%
All other majors	19.1%
Panel C: Computer Programmers (15-1131)	
Share of all H-1B Applications, 2010-2015	13.9%
Share of Occupation in College Major, 2010-2012	
Computer science	41.7%
Engineering	18.1%
Other business	6.2%
Math	6.0%
Business Management	4.0%
All other majors	24.0%

Notes: Based on author's calculations using the 2010-2012 American Community Survey and 2010-2015 Office of Foreign Labor Certification Disclosure Data for the H-1B Visa Program. To compare occupations across datasets, I first construct a crosswalk between the SOC codes found in the H-1B data and the ACS file. Each panel represents a different occupation. The share of the occupation in the H-1B data is calculated all applications from 2010-2015. The occupation-specific college major distributions are calculated using all workers aged 24-55 with a bachelor's degree or higher that are not living in group quarters and have a nonmissing occupation code.

Table B-3: Estimated Share of H-1B Visas, by College Major

Panel A: Broad Major Groups			
STEM	54.18	Liberal Arts	3.63
Business	20.51	Healthcare	2.90
Social Sciences	10.17	Education	2.39
Other	6.29		
Panel B: All College Majors			
Engineering*	21.03	Industrial and Commercial Arts	0.81
Computer Sci.*	20.17	General Educ	0.75
Other Business	6.39	Field Specific Educ	0.67
Life Sciences*	5.96	Liberal Arts and Humanities	0.67
Business Mgmt.	5.13	Sociology	0.66
Physical Sciences*	3.51	Languages	0.64
Math*	3.51	Philosophy	0.64
Accounting	2.87	Nursing	0.61
Communication	2.69	Protective Services	0.58
Finance	2.37	Architecture	0.58
Pschology	2.34	Agriculture/Forestry/Natural Resources	0.56
Economics	2.19	Pharmacy / Medical Prep	0.55
Technical Health Fields	1.74	Early and Elem. Educ	0.54
Poli. Sci./Intl Relations/Pre-Law/Legal Studies	1.70	Leisure Studies	0.42
Literature	1.68	Public Admin/Policy/Helath	0.26
Visual and Performing Arts	1.66	Social Work	0.24
Marketing	1.55	Family and Consumer Sciences	0.24
Other Fields	1.44	Other Educ	0.17
Social Science Fields, Other	1.20	Special Needs Educ	0.14
History	1.08	Secondary Educ	0.12

Notes: Based on author's calculations using the 2010-2012 American Community Survey and 2010-2015 Office of Foreign Labor Certification Disclosure Data for the H-1B Visa Program. See text for additional details on the data and the process to assign LCA data at the occupation level to specific college majors. Panel A provides estimated shares for the 7 broad college major groups from Table B-1. Panel B provides the shares used in analysis to construct the immigrant instrument for each of forty college majors. STEM majors are denoted by an asterisk.

Table B-4: H-1B Immigrant-Native Ratio Summary Statistics, By College Major

College Major	Mean	Minimum	Maximum	S.D
Computer Science	0.62	0.34	1.11	0.25
Math	0.31	0.18	0.78	0.18
Engineering	0.33	0.19	0.71	0.18
Life Sciences	0.09	0.05	0.18	0.04
Physical Sciences	0.21	0.14	0.46	0.12
Accounting	0.09	0.04	0.20	0.05
Economics	0.12	0.06	0.26	0.06
Finance	0.09	0.05	0.19	0.04
Marketing	0.05	0.03	0.10	0.02
Business Management	0.08	0.04	0.16	0.04
Other Business	0.09	0.05	0.20	0.05
Pharmacy & Medical Prep	0.11	0.05	0.29	0.07
Nursing	0.02	0.01	0.04	0.01
Technical Health Fields	0.06	0.04	0.13	0.03
Communication	0.04	0.02	0.10	0.02
Political Science, International Relations, Pre-Law & Legal Studies	0.05	0.03	0.11	0.03
Sociology	0.03	0.02	0.07	0.02
History	0.04	0.02	0.10	0.02
Pschology	0.04	0.02	0.08	0.02
Public Admin, Public Policy, and Public Helath	0.06	0.03	0.13	0.03
Social Work	0.02	0.01	0.04	0.01
Social Science Fields, Other	0.05	0.03	0.11	0.03
Philosophy	0.05	0.03	0.09	0.02
Liberal Arts and Humanities	0.04	0.02	0.08	0.02
Languages	0.07	0.04	0.14	0.03
Literature	0.05	0.03	0.10	0.02
Early and Elementary Education	0.01	0.01	0.03	0.01
Secondary Education	0.03	0.01	0.06	0.02
General Education	0.02	0.01	0.04	0.01
Field Specific Education	0.03	0.02	0.06	0.01
Special Needs Education	0.02	0.01	0.05	0.01
Other Education	0.05	0.02	0.11	0.03
Agriculture, Forestry, and Natural Resources	0.07	0.04	0.14	0.03
Architecture	0.08	0.04	0.17	0.04
Family and Consumer Sciences	0.02	0.01	0.05	0.01
Visual and Performing Arts	0.04	0.02	0.08	0.02
Leisure Studies	0.03	0.01	0.06	0.01
Industrial and Commercial Arts	0.06	0.03	0.15	0.03
Protective Services	0.02	0.01	0.05	0.01
Other Fields	0.07	0.04	0.17	0.04

Notes: Based on author's calculations using the 2010-2012 American Community Survey and 2010-2015 Office of Foreign Labor Certification Disclosure Data for the H-1B Visa Program. See text for additional details.

Table B-5: Occupational Task Classifications - O*NET 21.1

Detailed O*NET Activity	O*NET Element
Interactive (Peri and Sparber 2011)	
Oral Comprehension	1.A.1.a.1
Written Comprehension	1.A.1.a.2
Oral Expression	1.A.1.a.3
Written Expression	1.A.1.a.4
Communicating with Supervisors, Peers, or Subordinates	4.A.4.a.2
Communicating with Persons Outside Organization	4.A.4.a.3
Resolving Conflicts and Negotiating with Others	4.A.4.a.7
Quantitative (Peri and Sparber 2011)	
Deductive Reasoning	1.A.1.b.4
Inductive Reasoning	1.A.1.b.5
Mathematical Reasoning	1.A.1.c.1
Estimating the Quantifiable Characteristics of Products, Events, or Information	4.A.1.b.3
Analyzing Data or Information	4.A.2.a.4
Leadership	
Coordinating the Work and Activity of Others	4.A.4.b.1
Developing and Building Teams	4.A.4.b.2
Training and Teaching Others	4.A.4.b.3
Guiding Directing and Motivating Subordinates	4.A.4.b.4
Coaching and Developing Others	4.A.4.b.5
Staffing Organizational Units	4.A.4.c.2

Notes: O*NET Activities are categorized into related groups. The interactive and quantitative groups are defined following Peri and Sparber (2011). Additionally, I group six activities into a leadership index.

Table B-6: Sample Selection

Criterion	Observations Deleted	No. of Observations
Respondents in 2010-2012 3-Year ACS File		9,286,739
Drop those living in group quarters	394,580	8,892,159
Drop those not aged 24-64	4,083,768	4,808,391
Drop non-college graduates	3,291,221	1,517,170
Occupation Sample		
Drop those without valid Occupation	103,755	1,413,415
Employment Sample		
Drop those not in 1990-2008 cohorts	799,476	717,694
Drop natives born outside US	11,143	706,551
Natives	--	559,894
Immigrants	--	146,657
Earnings Sample		
Drop those still in school	81,170	625,381
Drop self-employed	77,449	547,932
Natives	--	440,308
Immigrants	--	107,624

Notes: Based on author's calculations using the 2010-2012 American Community Survey. The top set of criterion applies to all three samples. The employment and earnings samples include workers without valid occupations. All criterion used to select the employment sample are also used to select the earnings sample.

Table B-7: Number of ACS Observations in a Major-Experience Cell, By College Major

	Native Observations in Cell			Immigrant Observations in Cell		
College Major	Minimum	Maximum	Mean	Minimum	Maximum	Mean
Computer Science	549	1024	802.2	285	755	498.1
Math	267	393	325.4	119	221	155.8
Engineering	1540	2097	1762.1	937	1951	1337.1
Life Sciences	1364	2067	1847.8	343	673	536.2
Physical Sciences	423	507	459.9	224	400	285.3
Accounting	736	1310	954.4	331	582	405.5
Economics	420	704	524.5	175	343	247.3
Finance	546	803	683.0	95	218	163.1
Marketing	598	939	820.6	57	154	110.6
Business Management	1364	2381	1849.9	303	567	420.5
Other Business	1398	2061	1642.7	306	714	485.2
Pharmacy & Medical Prep	99	208	140.2	78	122	99.8
Nursing	823	1053	910.1	235	458	341.6
Technical Health Fields	713	905	824.6	144	249	196.4
Communication	1253	1987	1620.4	95	220	168.5
Political Science, International Relations, Pre-Law & Legal Studies	790	1203	953.9	97	196	146.7
Sociology	432	622	543.4	42	86	68.3
History	581	892	681.2	60	103	76.1
Pschology	1532	1906	1766.8	191	348	252.5
Public Admin, Public Policy, and Public Helath	101	144	120.2	13	35	25.1
Social Work	271	470	369.7	35	71	48.4
Social Science Fields, Other	535	721	657.8	66	126	97.0
Philosophy	322	482	380.9	46	114	78.3
Liberal Arts and Humanities	317	532	424.8	59	102	77.9
Languages	222	352	283.0	88	152	121.4
Literature	921	1302	1039.1	131	239	177.0
Early and Elementary Education	1062	1667	1348.6	78	140	110.9
Secondary Education	85	194	138.5	8	33	19.2
General Education	570	1091	849.9	153	265	195.2
Field Specific Education	669	798	732.2	73	134	103.2
Special Needs Education	140	235	179.1	6	24	14.1
Other Education	61	157	114.3	10	36	21.4
Agriculture, Forestry, and Natural Resources	218	322	268.6	26	62	38.3
Architecture	169	237	202.8	57	132	87.1
Family and Consumer Sciences	210	342	278.9	31	56	41.5
Visual and Performing Arts	858	1266	1055.6	131	222	186.7
Leisure Studies	208	582	407.8	7	44	26.6
Industrial and Commercial Arts	254	461	347.8	57	117	84.3
Protective Services	592	832	677.7	29	68	48.2
Other Fields	425	553	477.5	95	163	122.4
Full Sample	61	2381	736.7	6	1951	193.0

Notes: Based on author's calculations using the 2010-2012 American Community Survey. Each of the 40 college majors has 19 experience cells. The table lists the minimum, maximum, and average number of native and immigrant ACS observations in a major-experience cell.

C Theoretical Appendix

Consider the following production technology for a homogenous good. Final output Y is a function of non-labor inputs K (e.g., capital, materials, land) and a labor aggregate L.[19]

$$Y = A\left[\lambda K^{\delta} + (1-\lambda)L^{\delta}\right]^{1/\delta}, \tag{C-1}$$

where A is total factor productivity, $\lambda \in (0,1)$ is the relative productivity of capital, and the elasticity of substitution between capital and labor is defined as $\sigma_{KL} = 1/(1-\delta)$ and $\delta < 1$. The labor aggregate is made up of two different inputs, efficiency units supplied by low-skilled workers L^U (e.g., high school dropouts, high school graduates, and those with some college) and efficiency units supplied by high-skilled workers L^S, which are combined with the following CES function:

$$L = \left[\theta_U (L^U)^{\beta} + \theta_S (L^S)^{\beta}\right]^{1/\beta}. \tag{C-2}$$

The relative productivity of each input is given by θ_U and θ_S and are normalized to sum to one. The elasticity of substitution between low-skilled and high-skilled workers is defined as $\sigma_E = 1/(1-\beta)$ and $\beta < 1$.

In undergraduate and graduate studies, individuals specialize and accumulate different skills such that high-skilled workers are no longer perfectly substitutable. Suppose workers specialize in different majors m. The input L^S is then an additional CES function, which combines the inputs of workers with different majors

$$L^S = \left[\sum_m \theta_m (L_m)^{\eta}\right]^{1/\eta}, \tag{C-3}$$

where L_m is the efficiency units supplied and θ_m is the relative productivity of major m workers which are normalized to sum to one. The elasticity of substitution between workers with different majors is defined as $\sigma_M = 1/(1-\eta)$ and $\eta < 1$.

The final nest follows from the approach common to the literature. The input L_m is a final aggregation of workers with major m across different levels of experience x given by

$$L_m = \left[\sum_x \theta_{mx} (L_{mx})^{\phi}\right]^{1/\phi}, \tag{C-4}$$

where θ_{mx} is the relative productivity of workers with major m and experience x, which sum to one. The elasticity of substitution between high-skilled workers with the same major, but different levels of experience is defined as $\sigma_X = 1/(1-\phi)$ and $\phi < 1$.

The nesting order was chosen to divide workers that become increasing substitutable with one another. Ottaviano and Peri (2012) argue that the elasticity of substitution between different skill groups should increase with further nesting. Thus, the nesting structure assumes that two college graduates with different majors are more substitutable than high-skilled and low-skilled workers ($\sigma_E < \sigma_M$) but less substitutable than two workers with the same major and different years of

[19] I abstract from time and geographic subscripts for ease of exposition, but one could think about this occurring in an annual or decadal frequency with some level of geographic distinction - the nation, regions, commuting zones, or metropolitan areas.

experience ($\sigma_M < \sigma_X$).

In perfectly competitive labor markets, the wage of a particular input is equal to its marginal product. In this framework, the wage of a high-skilled worker with major m and experience x is

$$w_{mx} = \left[A(1-\lambda)Y^{1-\delta}L^{\delta-1}\right] \cdot \left[\theta_S L^{1-\beta}(L^S)^{\beta-1}\right] \cdot \left[\theta_m (L^S)^{1-\eta} L_m^{\eta-1}\right] \cdot \left[\theta_{mx} L_m^{1-\phi} L_{mx}^{\phi-1}\right]. \tag{C-5}$$

The first bracketed term is the marginal product of the labor aggregate in the production of the final output. The second bracketed term is the marginal product of high-skilled labor in producing the efficiency units of the overall labor input. Similarly, the third bracketed term is the marginal product of labor with major m in creating the high-skilled efficiency units. Finally, the last term represents the marginal product of experience x in creating the efficiency units of major m. Labor is supplied inelastically such that L_{mx} is equivalent to the labor supply of the group.

The labor demand curve expressed in Equation C-5 provides the functional form to analyze the wage effects of labor supply shifts from immigration. It is useful to think about how changes in relative supply of a skill group affects relative wages. The relative wages of workers with the same education, the same major, but different levels of experience *old* and *yng* is found by comparing Equation C-5 for both groups and is simplified as

$$\frac{w_{m,old}}{w_{m,yng}} = \left(\frac{\theta_{m,old}}{\theta_{m,yng}}\right)\left(\frac{L_{m,old}}{L_{m,yng}}\right)^{-\frac{1}{\sigma_X}}. \tag{C-6}$$

Equation C-6 shows that the relative wages between two groups in the same nest depend on their relative labor supplied, their relative productivities, and the elasticity of substitution between them. Importantly, the level of the wages in the preceding group, in this case highly-educated labor with major m, cannot be determined when making within-group comparisons. Because $\sigma_X > 0$, the theory predicts that an increase in the relative labor supply of a group will decrease their relative wage. This comparison is the focus of my empirical analysis.

Some additional assumptions are useful to empirically test this prediction. Suppose that the log relative productivity ($\ln \theta_{mx}$) is additively separable into a major-specific component μ_m, an experience-specific component ν_x, and a stochastic component ϵ_{mx} with mean zero such that $\ln \theta_{mx} = \mu_m + \nu_x + \epsilon_{mx}$. Taking the log of Equation C-5 and grouping like terms provides the following estimating equation:

$$\ln w_{mx} = \alpha + \psi_m + \nu_x - \frac{1}{\sigma_X}\ln L_{mx} + \epsilon_{mx}, \tag{C-7}$$

where $\alpha = \ln\left[A(1-\lambda)Y^{1-\delta}L^{\delta-1}\theta_S L^{1-\beta}(L^S)^{\beta-1}\right]$ and $\psi_m = \ln\left[\theta_m(L^S)^{1-\eta}L_m^{\eta-\phi}\right] + \mu_m$. Equation C-7 suggests that changes in wages of a particular major-experience group can be related to changes in the labor supply of that group, controlling for major- and experience-specific characteristics. Identifying the parameter σ_X requires an exogenous shifter of the labor supply. Immigrants are commonly used. Because data are not yet available to compare changes in major-experience wages over time, I adapt Equation C-7 accordingly

$$\ln w_{mx} = \alpha + \psi_m + \nu_x - \frac{1}{\sigma_X}p_{mx} + \epsilon_{mx}, \tag{C-8}$$

where $p_{mx} = dL_{mx}/L_{mx}$ is the supply shock to major m and experience group x. I assume that

$dL_{mx} = M_{mx}$ is the number of immigrants added to the major-experience group and use the number of natives (N_{mx}) as the pre-shock labor supply. I assume α, ψ_m and ν_x capture the counterfactual wage of the group. Thus, the corresponding regression compares deviations of log wages of the group to the relative supply shock experienced and the coefficient represents the inverse elasticity of substitution across experience groups.[20]

The effect on wages from a generalized supply-shift of workers with major m and experience x follows from differentiating Equation C-5 and is given by

$$d \ln w_{mx} = \frac{s_K}{\sigma_{KL}} d \ln K + \left(\frac{1}{\sigma_E} - \frac{s_K}{\sigma_{KL}} \right) \bar{m} + \left(\frac{1}{\sigma_M} - \frac{1}{\sigma_E} \right) m_S + \left(\frac{1}{\sigma_X} - \frac{1}{\sigma_M} \right) m_m - \frac{1}{\sigma_X} m_{mx}, \quad \text{(C-9)}$$

where $m_{mx} = dL_{mx}/L_{mx}$ is the supply shock to major m and experience x due to immigration. Supply shocks transmitted to higher levels of the production technology, m_m, m_S, and $\bar{m}$, are the average supply shocks of major groups, high-skilled workers, and all workers, respectively.[21]. Finally, s_K represents the income share accumulating to capital.

[20]It is common in the literature to include a final nest in the theoretical model that allows for imperfect substitutability between natives and immigrants within the same skill group. For ease of exposition, I omit that final nest. However, including that nest would change the interpretation of the regression coefficient. With the additional nest, the coefficient on p_{mx} would instead be $\left(\frac{1}{\sigma_F} - \frac{1}{\sigma_X} \right)$, where σ_F is the elasticity of substitution between similarly skilled immigrants and natives.

[21]Specifically, $m_m = \sum_x (s_{mx} m_{mx} / s_m)$ is the income-share weighted average immigrant shock for workers with college major m, where s_{mx} and s_m are the income shares accumulating to a major-experience and major skill group, respectively. Both m_S and $\bar{m}$ are analogously defined using the shock from the subsequent CES nest and the appropriate income shares.