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

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Abstract

This paper investigates the effect that high-skilled immigration has on the wages of U.S.-born college graduates. College-educated immigrants study different subjects in college than do natives. I present descriptive evidence that workers with different college majors compete in different labor markets. I adapt a standard model of the U.S. labor market to allow for the imperfect substitutability of workers with different college majors. Because immigrants are twice as likely as natives to major in STEM, the model predicts that the wages of native STEM majors should fall relative to other majors as skilled immigration increases. Using an IV strategy that takes advantage of large changes in the cap of H-1B visas and controls for major- and age-specific unobservable characteristics, I find that workers who are most exposed to increased competition from skilled immigration have lower wages than you would expect given their age and college major. A 10 percentage point increase in the immigrant-native ratio of a skill group decreases their relative wages by 1.2 percent. Overall, I estimate that STEM wages fell 4–12 percent relative to non-STEM wages because of immigration from 1990–2010.

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1 Introduction

Increasing the size of the STEM workforce has been a key strategy to maintain the economic competitiveness and growth of the U.S. economy.[1] 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). Despite the importance of this policy strategy in determining the size of the STEM workforce, surprisingly little is known about its labor market impact.

In this paper, I investigate the effect that immigration has on the wages of college-educated U.S.-born natives. I develop a straightforward model of the labor market, yielding the prediction that the relative wages of STEM majors should fall as additional high-skilled immigrants enter. I present descriptive evidence that workers with different college majors are imperfect substitutes, which implies that they are distinct factors of production. I adapt a production model of nested constant elasticity of substitution (CES) functions to incorporate this imperfect substitutability. My modeling choice is important because 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.[2] Because high-skilled immigration changes the ratio 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 by leveraging changes in the annual cap of H-1B visas combined with the fact that visa recipients are more likely to be STEM majors. I estimate

[1] STEM stands for Science, Technology, Engineering, and Mathematics. This paper focuses on bachelor's degree holders who studied STEM in undergraduate studies. The specific majors that I include in STEM are discussed in Section 2.1.

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

an instrumental variable (IV) model relating average log earnings to the size of immigrant inflows with college major and experience-cohort fixed effects. This specification thus compares major-experience groups with differently sized labor supply increases from immigration while controlling for major-specific unobservable characteristics and 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 you would expect given their age and college major. Specifically, I measure immigrant competition as the immigrant-native ratio in a major-experience 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 relative to quantitative tasks are more important for their job.

I also address the broader question of how immigration from 1990 to 2010 has affected the STEM wage premium. 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 wage gap between them. 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. The effect of immigration on native STEM major choice, however, appears to be small and isolated to particular subgroups (Orrenius and Zavodny, 2015; Ransom and Winters, 2016).

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.[3] 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. By focusing on tightly defined yet large skill groups, I find empirical evidence that changes 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.

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.

[3]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).

2 Theoretical Framework and Background

2.1 Defining Skill Groups

In order to affect relative wages, immigration must change the skill mix of the workforce. The standard approach is to group workers by their education (e.g., high school dropout, high school graduate, some college, college graduate, graduate/professional degree) and work experience using a set of nested CES functions (Borjas, 2014). In this framework, workers across skill groups are imperfect substitutes with one another. That is, they compete in separate labor markets and have complementary skills. There is disagreement, however, over how to group workers and these choices affect the way in which immigrants alter the skill mix.

Researchers disagree on how to define educational groups. Figure 1 shows that immigration has not altered the skill mix between high-skilled and low-skilled workers over the past five decades. The share of immigrants in the adult population has tracked closely to the share of immigrants among the college-educated. Thus, immigration will affect relative wages if there is imperfect substitutability within low-skilled or high-skilled groups. The literature has focused on whether high school dropouts and high school graduates are imperfect substitutes or just supply different levels of efficiency units. Borjas (2003) separates the two groups, which in turn concentrates any effects of immigration on the smaller group of native high school dropouts. On the other hand, Card (2009) argues that high school dropouts and graduates participate in the same labor market with the latter providing more efficiency units of labor, an approach more commonly taken in the labor literature (e.g., Katz and Murphy, 1992; Autor et al., 1998; Card and Lemieux, 2001)

This paper sidesteps that debate and focuses on imperfect substitutability among college-educated workers. Not all college graduates enter the labor market with the same set of skills. Computer programmers and historians are not perfect substitutes, even when conditioning on experience. Immigration has the potential to affect relative wages if immigrants tend to study different fields than native-born workers. To that end, this subsection documents large overrepresentation of immigrants in STEM fields and presents descriptive evidence that workers with the same college major have higher occupational overlap in comparison to all college-educated workers.

I separate workers into different skill groups based on their college major. In the American Community Survey (ACS), I observe the primary degree field of all college graduates. I divide workers into 40 detailed college majors, which make up seven broad college major classifications: STEM, Business, Healthcare, Social Sciences, Liberal Arts, Education, and Other. Table A-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.[4] For the remaining

[4] Of note, I include Computer Engineering graduates in Engineering, Actuarial Science graduates in Finance rather

fields, I largely follow groupings used by Blom et al. (2015).

Incorporating college major into the nested CES model will only improve our understanding of the wage effects of immigration if immigrants have different majors than natives. If immigrants have the same college major distribution as natives, the relative wages of different major groups would not change. However, they do not have the same distribution. Table 1 shows the distribution of college majors for the working-age population in the United States from 2010-2012 separately for natives (col. 1) and immigrants (col. 2). Strikingly, immigrants are nearly twice as likely to have studied a STEM field, 35.3% to 17.6%. This pattern holds whether you focus on men (49.7% to 26.4%) or women (21.8% to 9.9%). Conditional on studying in a non-STEM field, immigrants are overrepresented in Business and Healthcare and underrepresented in the Social Sciences and Education fields.

To demonstrate that college major better characterizes distinct factors of production, I show in Table 2 that occupations become more concentrated as the definition of skill group becomes more tightly defined. Occupations are given 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. Panel A considers the aggregate shares of the five largest occupations within a particular skill group. I vary the breadth of a skill group by constructing measures for (i) all workers, (ii) all college-educated workers, and (iii) each college major group. The share should be higher when the workers within a defined skill group are more substitutable. 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 the forty college majors and find an average share of 49 percent. Within the detailed major groups, occupations become more concentrated suggesting 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.[5] 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 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

than Math, and students from Health and Medical Preparatory Programs (i.e., Pre-Med) in Pharmacy.

[5]This measure has commonly been used to describe distributional overlap between groups. For instance, Borjas and Doran (2012) use the index to compare the similarity of the field of study of American mathematicians to the Soviet mathematics research agenda.

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% 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 begin to be 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. The pattern of increasing occupational overlap suggests that further dividing college-educated workers by college major is likely to increase within-group substitutability.

Grouping workers by their college majors has a particular advantage over simply grouping by occupation. It would not be difficult to categorize occupations into a subset of skill groups. However, this approach is not appropriate here. There is substantial evidence that natives respond to immigration by switching occupation (e.g., Peri and Sparber, 2009, 2011), which makes it difficult to estimate the effect of immigration on wages. Conversely, college major is largely a predetermined characteristic once workers enter the labor force, although there is the potential that workers return to school to earn a bachelor's in a new field or pursue graduate studies. However, 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 section argues two points: (1) distributional differences in college majors between natives and immigrants mean that some natives may be more affected by immigration than others and (2) college-educated workers with the same major tend to work in similar occupations. Adapting the nested CES model to incorporate imperfect substitutability between workers with different college majors could shed new light on these distributional effects. The following section presents such a model.

2.2 Theoretical Framework

2.2.1 The Model

Textbook theory suggests that immigration should lower the relative wages of workers that most intensely compete with immigrants and increase the relative wages of complementary workers. In order to make estimation tractable, the common approach is to model a competitive labor market by combining workers of different skill types within a set of nested CES functions to produce

a homogenized aggregate labor input.[6] In this framework, workers are grouped based on educational attainment and experience and all workers within the same group are assumed to be perfect substitutes. Section 2.1 provided descriptive evidence that further dividing the highly-educated by their college major better meets this assumptions. Furthermore, this division matters because immigrants tend to study different fields than natives. I build on earlier work by adding a nest to the production technology that allows for highly educated workers with different college majors to be imperfectly substitutable.

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.[7]

$$Y = A\left[\lambda K^{\delta} + (1-\lambda)L^{\delta}\right]^{1/\delta}, \tag{2}$$

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 $\delta < 1$.[8] 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:

$$L = \left[\theta_U (L^U)^{\beta} + \theta_S (L^S)^{\beta}\right]^{1/\beta}. \tag{3}$$

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, even within experience groups, 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

$$L^S = \left[\sum_m \theta_m (L_m)^{\eta}\right]^{1/\eta}, \tag{4}$$

where L_m is the efficiency units supplied and θ_m is the relative productivity of major m workers

[6] This approach has been widely used in the immigration literature. See Borjas (2003), Ottaviano and Peri (2012), Manacorda et al. (2012), Borjas (2014), and Sparber (Forthcoming) for examples.

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

[8] It is common to assume this function is Cobb-Douglas ($\sigma_{KL} = 1$) and the labor share is 0.3. Since this paper is concerned with relative wages, the assumption is not needed here.

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

$$L_m = \left[\sum_x \theta_{mx} (L_{mx})^{\phi} \right]^{1/\phi}, \tag{5}$$

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 $\phi < 1$.

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

$$w_{mx} = \left[A(1-\lambda) Y^{1-\delta} L^{\delta-1} \right] \cdot \left[\theta_S L^{1-\beta} (L^S)^{\beta-1} \right] \cdot \left[\theta_m (L^S)^{1-\eta} L_m^{\eta-1} \right] \cdot \left[\theta_{mx} L_m^{1-\phi} L_{mx}^{\phi-1} \right]. \tag{6}$$

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.[9]

2.2.2 Wage Effects

I now highlight how the nested CES approach simplifies and restricts the ways in which changes in labor supply affect wages.[10] The model allows for an easy comparison of wages of different types of labor inputs, but provides no information on the absolute level of wages. So, I use the model to address two questions: (1) do the wages of natives that experience relatively large immigrant shocks fall relative to other groups and (2) how has immigration affected the relative wages of STEM and non-STEM workers. First, 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 6 for both groups and is simplified as

$$\frac{w_{m,old}}{w_{m,yng}} = \left(\frac{\theta_{m,old}}{\theta_{m,yng}} \right) \left(\frac{L_{m,old}}{L_{m,yng}} \right)^{-\frac{1}{\sigma_X}}. \tag{7}$$

[9] While this assumption is useful for focusing on wage effects, Dustmann et al. (2016) show that this assumption may be restrictive if the labor supply elasticity varies across groups.

[10] For a more detailed exposition of these points, see Borjas (2014).

Equation 7 shows that the relative wages between two groups in the same nest depend on the relative supplies and productivities of the two groups 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 $\ln \theta_{mx} = \mu_m + \nu_x + \epsilon_{mx}$.[11] Taking the log of Equation 6 and grouping like terms provides the following estimating equation:

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

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 8 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 8 accordingly

$$\ln w_{mx} = \alpha + \psi_m + \nu_x - \frac{1}{\sigma_X} p_{mx} + \epsilon_{mx}, \tag{9}$$

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.

However, immigrants endogenously enter skill cells. In particular, immigrants choose to migrate to the U.S. when demand conditions for their skills are favorable. Their choice introduces a positive bias in estimation, a result demonstrated in recent work by Llull (Forthcoming). Thus, an instrument is needed to predict immigrant entry. Section 2.3 highlights features of the H-1B visa program that I use to construct such an instrument. Having identified an approach to address the first question, I now turn to the second.

While the model allows for empirical estimation at higher levels of the nest (e.g., comparisons across majors), it is often not tractable due to the corresponding reduction in observations. However,

[11] This assumption is potentially restrictive. In application, I allow for the relative productivities to evolve linearly specific to each major.

given parameters of the model, one can simulate relative wage effects at those higher levels. The effect on wages from a generalized supply-shift from immigration are characterized in Borjas (2014). Adapting his model to include the college major nest, the effect on the wage of workers with major m and experience x is

$$d\ln w_{mx} = \frac{s_K}{\sigma_{KL}} d\ln K + \left(\frac{1}{\sigma_E} - \frac{s_K}{\sigma_{KL}}\right)\bar{m} + \left(\frac{1}{\sigma_M} - \frac{1}{\sigma_E}\right) m_S + \left(\frac{1}{\sigma_X} - \frac{1}{\sigma_M}\right) m_m - \frac{1}{\sigma_X} m_{mx}, \quad (10)$$

where $m_{mx} = dL_{mx}/L_{mx}$ is the supply shock to major m and experience x due to immigration. Additionally, the 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.[12]. Finally, s_K represents the income share accumulating to capital.

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 on a particular group of workers. Equation 10 shows that the total wage effect of immigration relies on four elasticities and the income shares of each group. Importantly, higher-level terms cancel out when comparing two groups from the same nest. The first two terms in the wage equation are common to all low-skilled and high-skilled workers. The third and fourth terms are common to all high-skilled workers and all workers with major m, respectively.

Suppose there are only two distinct majors, STEM and non-STEM. By averaging Equation 6 over experience groups within those two majors and taking the difference, the relative wage effect between STEM and non-STEM workers due to a generalized immigration shock is

$$d\ln w_{\text{STEM}} - d\ln w_{\text{non-STEM}} = -\frac{1}{\sigma_M}\left(m_{\text{STEM}} - m_{\text{non-STEM}}\right). \quad (11)$$

The relative wage of the major with the smaller immigrant shock will increase. The magnitude of the relative wage effect 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. Importantly, the elasticity from the lower nest, σ_X, does not affect the relative wages directly, but only by determining how immigrant shocks at the experience level pass through to shocks at the major level. In Section 5, I discuss how I estimate σ_M, m_{STEM}, and $m_{\text{non-STEM}}$ and simulate the effect of immigration from 1990 to 2010 on the STEM wage premium.

Finally, it is important to note an important way in which immigration could affect wages

[12]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.

that cannot be detected in this framework. It could be that immigrants bring ideas or generate intermediate inputs that have positive productivity gains. Indeed, Khanna and Morales (2017) argue that, by largely working in the IT sector, H-1B immigrants generate innovations (e.g., software) that improve overall productivity. In its simplest form, this could be seen as immigration directly impacting the level of total factor productivity, A, in Equation 2. However, as just noted, any within-group wage comparison will net out this overall effect of immigration.

2.3 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 great 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% 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% 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% of temporary work visas (Hunt, 2017).[13] These descriptive facts suggest that historic changes to the annual H-1B visa cap affect 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.[14] The visa is awarded to firm-sponsored workers in "specialty occupations" that require specialized skills and at least a bachelor's degree. These occupations are primarily 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 exogenous variation in the number of immigrants, changes in the cap and the occupational distribution of visa applications.

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. In 1998, the American Competitiveness and Workforce Improvement Act temporarily increased the cap to 115,000 for fiscal years 1999 and 2000.[15] In 2000, the American Competitiveness in the 21st Century Act (AC21) further increased the cap to 195,000 for fiscal years 2001, 2002, and 2003. In the following year, the ex-

[13]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.

[14]The number of approved H-1B visas can exceed the cap in any given year. Both universities and non-profit organizations are currently exempt from the cap, as are visa renewals and employer changes.

[15]The U.S. government fiscal year begins in October. The H-1B application period begins in the preceding April.

pansion 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. While the cap was not binding in the early 1990s, it was for a number of years in the late 1990s and has been since the cap decreased in 2004 (Kerr and Lincoln, 2010).

STEM occupations receive the majority of H-1B visas. To receive an H-1B visa, firms sponsor specific individuals to work in the U.S. and file the 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 A-2) followed closely by "Software Developers, Applications, and Systems Software" (17.1%) and "Computer Programmers" (13.9%).

I use changes in the annual cap and the fact that H-1B visas tend to go to STEM occupations to provide exogenous variation in the number of immigrants in a major-experience cell. Unfortunately, the college major of H-1B applicants is not observable in the LCA data. So, I estimate the share of H-1B visas going to a particular college major by using the six-digit SOC code included on the 2010-2015 LCA data and by assigning the types of college majors that individuals with these occupations tend to have. Specifically, I estimate the share of H-1B visas being awarded to college major m as:

$$\hat{\text{Share}}_m^{\text{H-1B}} = \sum_{\text{all } k} \left(\frac{\text{H-1B Applications}_k^{2010-15}}{\text{H-1B Applications}^{2010-15}} \right) * \left(\frac{\text{Population}_{km}^{24-55}}{\text{Population}_k^{24-55}} \right), \tag{12}$$

where the first term in the summation is the share of all H-1B applications that are for occupation k and is estimated by pooling all applications from the 2010-2015 LCA data. The second term is the share of workers in occupation k that studied major m and is estimated with the 2010-2012 American Community Survey using college graduates aged 25 to 55.[16]

Table A-2 highlights this approach for the three largest H-1B occupations already mentioned. Panel A shows that 21.4% of "Computer and Information Research Scientists" studied Computer Science, with Engineering being the second most prominent major at 16%. 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%).

[16]The choice of age group is admittedly arbitrary, but 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.

The estimated share of H-1B visas awarded to each college major are reported in Table A-3. Panel A reports the estimated share for each of the seven broad major groups and Panel B reports the share for all forty college majors that are used for analysis. Not surprisingly, I estimate that the majority of H-1B visas are awarded to STEM majors (54.18%). Engineering and Computer Science majors are the most prominent college majors at 21.03% and 20.17%, respectively. The second largest major group is Business, with Other Business at 6.39% and Business Management at 5.13% being the largest majors in the group. The smallest college major group to estimated to receive H-1B visas are Education majors (2.39%) with Secondary Education majors receiving the smallest share (0.12%).

Interacting these shares with the annual cap predicts the number of H-1B immigrants arriving each year with a particular major. Specifically,

$$\hat{M}_{mx} = \hat{\text{Share}}_m^{\text{H-1B}} * \text{H-1B Cap}_x \tag{13}$$

The variation of the instrument is demonstrated in Figure 2. For ease of exposition, I plot the data for the seven broad major groups. The left panel displays the predicted number of immigrants $\hat{M}_{mx}$ in thousands of immigrants. The solid line represents the total H-1B visa cap in October of each calendar year. The lines below represent how the cap is divided into different college majors based on the estimated college major share. Most of the cap is allotted to STEM and Business majors. The right panel displays the instrument used in analysis, p_{mx}^{IV}, which is the ratio of the value in the left panel and the number of native workers present in the major-year cell. The solid line represents the average immigrant shock, weighted by population. STEM majors experience the largest and most variable shock over time, ranging from about 20% to 60% of the major-year native population.

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. This means that workers can reside in the U.S. with a nonimmigrant status while simultaneously applying for permanent residency.[17] 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 (i.e., China and India), the process of status adjustment can be lengthy.[18] Upon applying for an immigrant visa, individuals receive a Priority Date, which signifies their place in line for an available

[17] In official parlance, a nonimmigrant is an individual in the U.S. on a temporary basis. An immigrant is someone with permanent residency who resides in the U.S. for a longer period of time.

[18] IA90 kept in place country-specific caps on immigration. By law, no more than 7% of all immigrant visas can be awarded to immigrants from a single country. Given their size and importance as sending countries of skilled workers, this cap is particularly binding for individuals from India and China.

visa. 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.

This section introduced a new way to group workers, which better matches the assumptions of the theoretical model. Changes in the H-1B visa program provide plausibly exogenous variation in the stock of immigrants across different college majors. 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 a large immigrant shock relative to those that experienced a smaller immigrant shock, 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 college major groups 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 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.

Administrative data on the H-1B visa program come from the Office of Foreign Labor Certification (OFLC) Disclosure Data. 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.[19] 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.

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 1990 and 2008. 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.[20][21]

3.1.2 Definition of sample, key outcome variables and treatment

Sample—The main analysis sample includes college-educated natives and immigrants[22] divided into skill groups based on their college major and U.S. labor market experience. Outcomes are averaged over individuals within a skill group. The unit of analysis is a major-experience group. A method to group workers by college major was presented in Section 2.1. 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.[23] That year defines the experience cohort of all natives and any immigrants 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. This 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 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 sample to only include individuals whose wage is set by the market, excluding self-employed

[19] Data for program years 2001-2007 are available at `http://www.flcdatacenter.com/CaseH1B.aspx`. For all later program years, data can be accessed at `https://www.foreignlaborcert.doleta.gov/performancedata.cfm`.

[20] The O*NET production database is publicly available and can be downloaded at `http://www.onetcenter.org/dictionary/21.1/excel/`.

[21] I combine some SOC codes to build a crosswalk between the 2010-2012 ACS, the O*NET production database, and the OFLC Disclosure Data.

[22] An individual is considered to be an immigrant if they are a naturalized citizen or not a citizen.

[23] While this cutoff is somewhat arbitrary, unreported results are robust to choosing age 23 or by incorporating quarter of birth to split the difference.

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 and remove individuals with top-coded income. 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 three measures of native employment: the employment rate, the full-time 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 code an individual as full-time if they worked at least 40 weeks over the previous year and at least 35 hours in a usual week.[24] Because a range of weeks is observed in the ACS, I impute the specific number of weeks worked by assigning individuals the midpoint of their range. Finally, 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 1990 and 2010 and assign an individual their occupation's average. I also use the percentile rank of average earnings for the occupation in 1990 and 2010 and assign these ranks to an individual.

I measure the skill content of occupations using O*NET data and construct three variables. The first variable compares the importance of interactive tasks relative to complex cognitive tasks and follows the classification used by Caines et al. (2016). The second variable compares the importance of interactive tasks and skills relative to quantitative tasks and skills as defined by Peri and Sparber (2011). Because Caines et al. (2016) include a number of supervisory activities in the complex cognitive group, I create an additional group with activities related to leadership and management. The activities used in the leadership aggregate can be found in Table A-4. 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-cohort then divided to create the ratio.

Treatment—I define the immigrant shock in a major-experience group to be the ratio of the number of immigrants in the group to the number of natives. 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 (Borjas, 2014) is the immigrant share, the ratio of immigrants to the total labor supply of the group (including immigrants). As a

[24]The ACS asks respondents how many hours they worked in a "usual" week over the last 12 months.

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:

$$\ln w_{mx}^{N} = \mu_m + \chi_x + x \cdot \mu_m + \beta p_{mx} + \epsilon_{mx} \tag{14}$$

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 control for the wage-experience profile of all college-educated workers. Additionally, major-specific linear cohort trends, $x \cdot \mu_m$, 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. The CES framework from Section 2.2 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 the 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 instrumental variable (IV) strategy that leverages national changes in the H-1B visa cap. These changes affect the arrival of immigrants

into the U.S. and thus the stock of immigrants in 2010-2012. The key insight is that H-1B visas are predominately awarded to workers in certain occupations. H-1B visas tend to go toward STEM occupations. Figure 2 showed that STEM majors were most affected by policy changes. The instrument is defined by $p_{mx}^{IV} = \hat{M}_{mx}/N_{mx}$ where $\hat{M}_{mx}$ is the predicted number of immigrants with college major m that entered the U.S. with experience cohort x due to the H-1B visa program (see Equation 13).

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

$$p_{mx} = \mu_m + \chi_x + x \cdot \mu_m + \theta p_{mx}^{IV} + u_{mx} \tag{15}$$

and the second-stage is given by Equation 14. Identification of the second stage requires a strong correlation between the predicted H-1B immigrant shock, p_{mx}^{IV}, and the actual immigrant shock, p_{mx}. Figure 3 plots the first-stage relationship between the instrumented immigrant shock, using changes in the H-1B program, and the actual immigrant shock, net of major and cohort fixed effects. The dashed line in this figure represents the forty-five degree line. The solid line demonstrates the positive relationship between the predicted and actual immigrant shocks. 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 shock is associated with a 6.69 percentage point increase in the actual immigrant shock in 2010 (F-stat=11.39). Column 2 controls for the major-specific unemployment rate at labor market entry, which only slightly changes the estimate. Finally, column 3 adds major-specific linear cohort trends. The first-stage coefficient decreases in magnitude and loses some significance. However, the estimate is still significant at the 5 percent level (F-stat=6.20). The weaker significance in column 3 introduces a concern about weak instruments. However, Bound et al. (1995) shows that the weak instruments bias is in the direction of OLS. Because OLS likely suffers from a positive bias, weak instruments bias away from finding a negative effect. 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 instrument is similar to the supply-push instrument commonly used in the literature in that it is an interaction between a supply shifter and a fixed share that divides immigrants across space.[25] Rather than relying on the endogenous decision of immigrant arrival at the national level, it takes advantage of changes in national-level policy.

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. Major fixed effects control for changes in the wage structure that affect the wages of all workers within a major. Given the instrument and data availability, I am unable to control for unobservable characteristics at the major-experience level. I allow for differential returns to experience across college major by controlling for any major-specific linear trends that may bias estimation. Additionally, I construct major-specific unemployment rates for the year a cohort entered the U.S. labor market, which controls for major-specific labor market conditions that are contemporaneous with 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 skills they possess, then the estimate will be biased away from a negative effect. The remaining concern is any major-experience wage shock that is not correlated with the major-specific employment rate and is 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. However, controlling for the major-specific unemployment rate suggests this is not particularly concerning. Table 3 shows a significant negative correlation between the major-specific unemployment rate and the actual immigrant shock. Additionally, the major-specific unemployment rate is negatively correlated with current earnings and is insignificant. If anything, the positive correlation between immigration and improving labor market conditions would result in a positive bias. Finally, column 4 of Table 3 shows the relationship between the unemployment rate at arrival

[25] The supply-push IV common in the literature allocates immigrants in geographic space based on historical settlement patterns by country. Here, I allocate immigrants into idea space based on the historical pattern of STEM immigrants receiving H-1B visas.

and the instrument. It is encouraging that the effect of this control on the instrument is insignificant.

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 robust standard errors that are clustered at the college major level, which allow for within-major correlation of error terms across cohorts.

4 Results

4.1 Earnings

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.[26] As previously discussed, one might be concerned that the 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 reduced-form relationship between the predicted immigrant shock from changes in the H-1B visa program and native earnings. Strikingly, the relationship reverses and reveals a negative impact of immigration on wages. Figure 4 paints a clear picture. The 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 4 presents weighted least squares and two-stage weighted least squares estimates of the effect of high-skilled immigration on native earnings. Panel A presents earnings results where the dependent variable is the average log weekly earnings of natives in each 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.[27] Column 1 presents the estimate from weighted least squares controlling for college major and cohort fixed effects. The estimate is positive (0.0343),

[26] As discussed in Section 3.2.2, the dependent variable is measured with increased precision in major-cohort cells that contain more native observations. Unless otherwise mentioned, all specifications are weighted by the number of native observations in the major-cohort cell.

[27] 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.

but statistically insignificant. Controlling for the major-specific unemployment rate increases the point estimate (col. 2) and additionally controlling for major-specific linear cohort trends reduces the coefficient to 0.009 (col. 3). Column 4 instruments for the actual immigrant shock with the predicted immigrant shock based on changes in the H-1B policy. This estimate corresponds to the slope in Figure 4. The point estimate (-0.0641) is negative and statistically significant at the 5 percent level. Column 6 presents results that control for both the unemployment rate and linear trends. The estimate is -0.118 and is significant at the 5 percent level.

Section 3.2 highlights that this is 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, a 25 percentage point increase, decreases relative earnings by about 3 percent. The H-1B program had the largest impact on the supply of workers in the Computer Science field. The immigrant-native ratio for Computer Science majors increased from about 0.35 for early 1990s cohorts to about 0.85 at the peak of the H-1B cap in the late 1990s and early 2000s cohorts, decreasing relative wages by about 6 percent.

Results are robust to different measures of group-specific earnings. The remainder of Table 4 presents estimates using different earnings measures. Panel B presents results where the dependent variable is average log annual earnings and Panel C uses average log hourly earnings. In both panels, the results are qualitatively similar and estimates range from -0.635 to -0.127 and are measured with similar precision to average log weekly earnings.

The results are also robust to alternative specifications. In my main analysis, the treatment variable is the size of the immigrant shock relative to the native population. Table A-5 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 (cols. 3 and 4) or by measuring treatment as the share of the immigrant population (cols. 5 and 6) as done in Borjas (2003). Estimates using this measure are similar in magnitude, but are statistically insignificant. The results are also robust to using median log weekly earnings as the dependent variable (cols. 7 and 8). Additionally, the results presented in Table A-6 shows similar results when using no weights or other weighting schemes.

Earlier work suggests that the effect of high-skilled immigration is heterogenous across subgroups of natives (Orrenius and Zavodny, 2015; Ransom and Winters, 2016). Table 5 explores the possibility of heterogenous effects by focusing on the average log weekly earnings of specific native subgroups. 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 -0.168 and is significant at the 1 percent level (column 2). The point estimate for native women and white natives remains negative, but lacks precision. Finally, the estimate on black natives is

small, insignificant, and reasonably sized negative values cannot be rejected.[28]

4.2 Employment

Section 4.1 documents a negative relationship between the size of an immigration shock and the relative wages of native-born workers. This result might be driven by employment effects on the extensive or intensive margin. Table 6 reports results on employment outcomes for all natives. I consider three measures for each major-experience group: the share employed, the share working full-time, and the average full-time equivalency index for the cell, where unity represents working 2,000 hours in a year. For each measure, I present weighted least squares and two-stage weighted least squares results that include major and cohort fixed effects. Each row represents a different grouping of natives.

The estimate in column 2 suggests that the immigrant shock is associated with an increase in the probability of working for all natives. The 2SLS estimate is 0.079 and is significant at the 10 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). When considering the effect of employment across native subgroups, all groups have a positive effect, but it is only significant for white natives. The estimates on full-time employment for all natives are close to zero and insignificant (cols. 3 and 4), although there is evidence of a negative effect on native men. There is a similar pattern when considering the effect on the index of hours worked in a year. Overall, the table shows some evidence that immigration increased the likelihood of working, but decreased the amount of hours worked throughout the entire year.

4.3 Type of Work

Immigration may not only affect wages and whether or not an individual works, but it may also affect the type of work they do. In response to immigration, natives may move out of occupations where immigrants have a comparative advantage. This section explores how immigration affected the occupations of natives. In particular, I ask to what extent natives work in lower paying occupation and how the skill content of these occupations has changed.

Table 7 explores whether the earnings effect is driven by natives moving into lower paying occupations. Column 1 duplicates the result from Table 4 using own earnings. The wage effect can be decomposed into two elements: a within-occupation effect and a between-occupation effect.

[28] 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 for black natives.

I assign natives the average log weekly earnings of their occupation from 1990, which isolates the second effect. Column 2 shows that about three-quarters of the wage effect comes from natives working in lower paying occupations. This result is robust to using occupational average earnings from the 2010-2012 ACS (col. 3) or by constructing the percentile rank of occupational earnings in 1990 or 2010 (cols. 4 and 5).

While occupations group workers by specific job categories, I also explore whether the underlying tasks that natives complete are affected by immigration in Table 8. In particular, I compare the relative importance of interactive or leadership tasks to cognitive or quantitative tasks. Each column represents a different comparison. Column 1 uses a classification from Caines et al. (2016) and compares interactive to complex cognitive tasks. The second column uses the classification from Peri and Sparber (2011). While there is some overlap between these groupings, they have their differences. In particular, Caines et al. (2016) includes supervisory activities such as "Coordinating the Work and Activities of Others" and "Guiding, Directing and Motivating Subordinates" in the complex cognitive grouping. I gather these and other activities into a group that I term "Leadership" tasks and compare this index to the quantitative index from Peri and Sparber (2011).

I find evidence that immigration causes U.S.-born workers to skew more toward interactive or leadership tasks, relative to quantitative tasks. All three point estimates are positive and significant when considering all natives (Panel A). In the male native sample, only the leadership-quantitative relationship is significant, though all are positive. This suggests that switching to leadership or supervisory roles is particularly important for men.[29] 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. Table A-7 reports results for the underlying tasks and abilities individually.

This section presents broad 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 work in occupations where interactive or leadership tasks are important relative to quantitative tasks. The identification strategy allows for clean estimation of these causal effects. However, the question of how high-skilled immigration more broadly affects an entire major group remains. Since 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.

[29]Note that some of the leadership activities are included in the complex cognitive group used in column 1 and not included in either group in the second column.

5 Simulation

While the previous section documents a negative causal relationship between immigration and wages, the question of how high-skilled immigration affected the wages of workers across different college majors remains. Given data availability, this question cannot be addressed using the empirical strategy above. Answering this requires returning to the structure of the nested CES model. Section 2.2.2 shows how the relative immigrant shocks of two skill groups are related to changes in their relative wages by the elasticity of substitution between the groups. In this section, 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. To do this, I first need to estimate the elasticity of substitution between STEM and non-STEM workers. With estimates in hand, I can compare the size of the immigrant shock of STEM workers to non-STEM workers to get the magnitudes of the relative wage effect.

5.1 Estimates of σ_M

In Equation 11, the relative wage effect between STEM and non-STEM workers requires an estimate of the elasticity of substitution between these two groups. To my knowledge, this 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-skill cell is likely endogenous. Immigrants could choose to enter the U.S. and locate to a state where returns to their skills are higher in that year. Additionally, natives may choose to relocate in response to immigrants or wage offers in other locations. While credibly estimating this parameter is beyond the scope of this paper, I can 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 (Forthcoming) 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. The estimate from Table 4, Panel A, Column 6 suggests a value closer to 10. However, my estimate is likely higher because workers are grouped into single-year cohorts which would lend toward more substitutability between groups. Given the values used in these other papers, 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 of STEM and non-STEM degrees across 51 states (incl. D.C.) in the United States in two time periods using data from the 2010-2012 and 2013-2015 ACS. Table 9 provides estimates from this approach. All specifications include state and period fixed effects weight observations using the number of ACS observations or the variance weight from Borjas et al. (2012). For columns 1 and 2, I measure the labor inputs using log relative hours worked by STEM and non-STEM graduates. The CES frameworks suggests that the appropriate measure is the relative efficiency units supplied by each input, which is given by Equation 5. This requires estimates of the relative productivity of the experience groups. To estimate these, I replicate the approach from Borjas (2014) which uses data across the 1960-2000 censuses and the 2010 3-year ACS. I then aggregate hours worked across different experience groups using Equation 5, the estimated productivity parameters, and a value of 6.54 for the elasticity of substitution across experience groups.[30] Columns 3 and 4 present estimates using the constructed efficiency units.

The estimated value of σ_M depends the wage sample used. Panel A presents results using all workers wages. The estimates range between 4.57 and 5.38 and do not substantially vary with different labor input measures 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 3.69. Importantly, these estimates fall within the range prescribed by theory. In practice, 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).

5.2 Relative Wage Effects

With values of σ_M in hand, the remaining piece 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

[30] In his simulations, Borjas (2014) uses a value of 6.7 for the elasticity of substitution between experience groups. However, his estimate of the inverse of this elasticity in Table 5.1 is 0.153, which suggests an elasticity of 6.54. I use this value for σ_X.

occupation.[31] 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.[32] 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 10 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 increase in relative wages varies from 12.1 percent, when STEM and non-STEM workers are not very substitutable, to 3.6 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 2.2 percent and 7.3 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 US 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 grouped by their college major. 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. This effect is driven by natives switching to lower paying occupations that require more manual and interactive tasks. More broadly, immigration over the past two decades has decreased the wages of STEM graduates by 4 to 12 percent relative to non-STEM workers.

This paper is the first to empirically explore how immigration differentially affects STEM and non-STEM graduates. Earlier work treated college-educated natives as a single group (e.g., Borjas,

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

[32] Since college major is only observable in the 2010 data, I construct income shares using that data set. The weighting strategy relies on a first-order approximation. The income share of each input changes with relative labor supply. Ideally, one would use the income share from a middle period (i.e., the 2000 census) to get a better approximation.

2003; Ottaviano and Peri, 2012) or looked at earnings and employment effects on native STEM graduates only (Ransom and Winters, 2016). I implement an estimation strategy that allows for analysis of the wage effects of immigration at the national level, while instrumenting for the endogenous presence of immigrants within major-experience groups. Notably, this approach uncovers a negative relative wage effect that is consistent with the underlying theory.

The approach used in this paper, grouping workers by college major, has applications in other strands of the immigration literature. Hanson and Slaughter (2016) consider whether STEM immigrants assimilate faster than non-STEM immigrants. Because of occupational switching, they could be overestimating the speed at which STEM immigrants assimilate. The categorization of skill in this paper allows for a cleaner analysis of immigrant assimilation.

The findings of this paper have 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. As Section 2.2.2 makes clear, the comparison used in the empirical analysis nets out the overall wage effect of immigration and there is strong evidence to suggest it is positive. Immigration could have a crowding-in effect at the firm level (Kerr and Lincoln, 2010; Kerr et al., 2015), although there is mixed evidence (Doran et al., 2016), and immigrants in the information technology sector have positive effects on innovation, which increases overall productivity (Bound et al., 2017; Khanna and Morales, 2017). It is likely that the seemingly large positive productivity effects outweigh the negative distributional effects described in this paper.

However, this paper sheds light on the distributional consequences of high-skilled immigration that are particularly important in the current policy debate on changing the criteria used to determine who can enter the United States. I find negative relative wage effects for STEM workers. As the relative wages of STEM workers fall, the marginal student may switch from STEM to non-STEM fields of study. If STEM graduates are an important component of innovation in the economy, policies to increase native STEM degree completion could be even more important in maintaining a pipeline of STEM workers in the presence of immigration.

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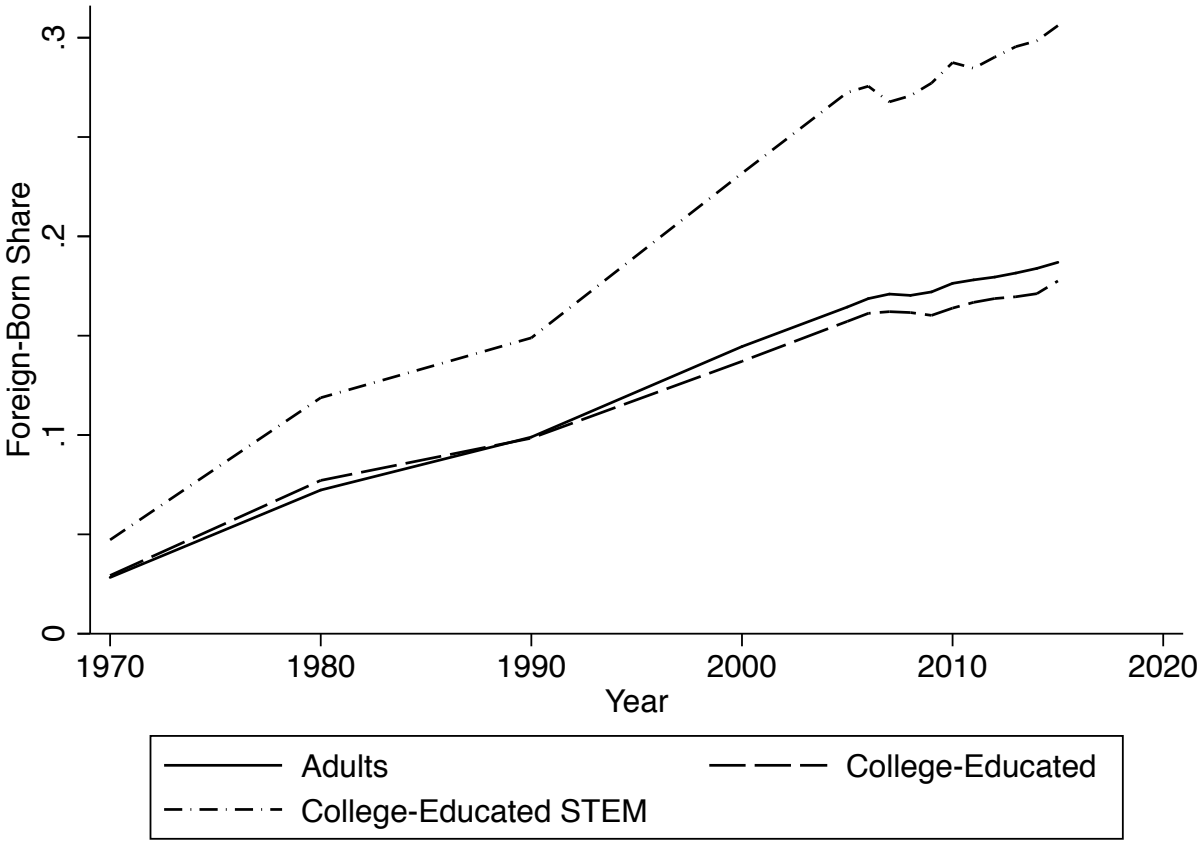
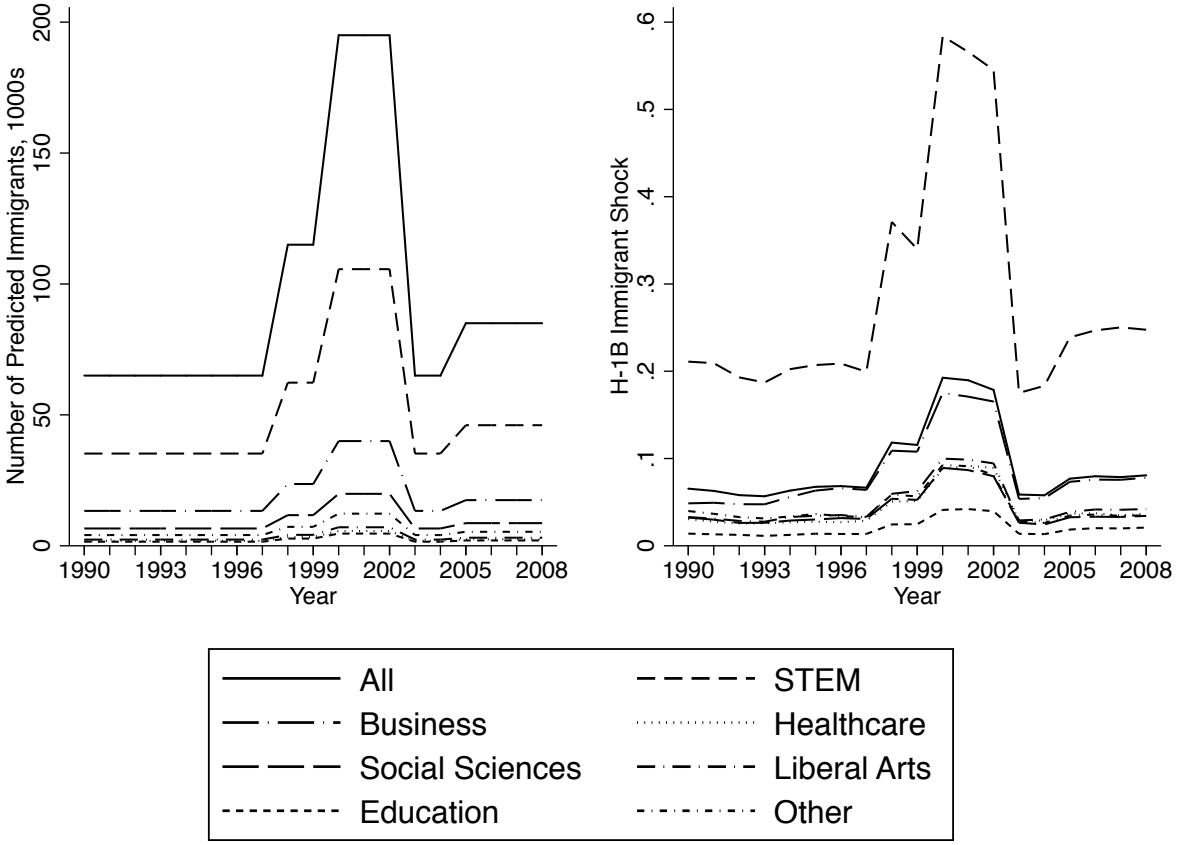
Figure 1: Share of Foreign-Born Adults, 1960-2015



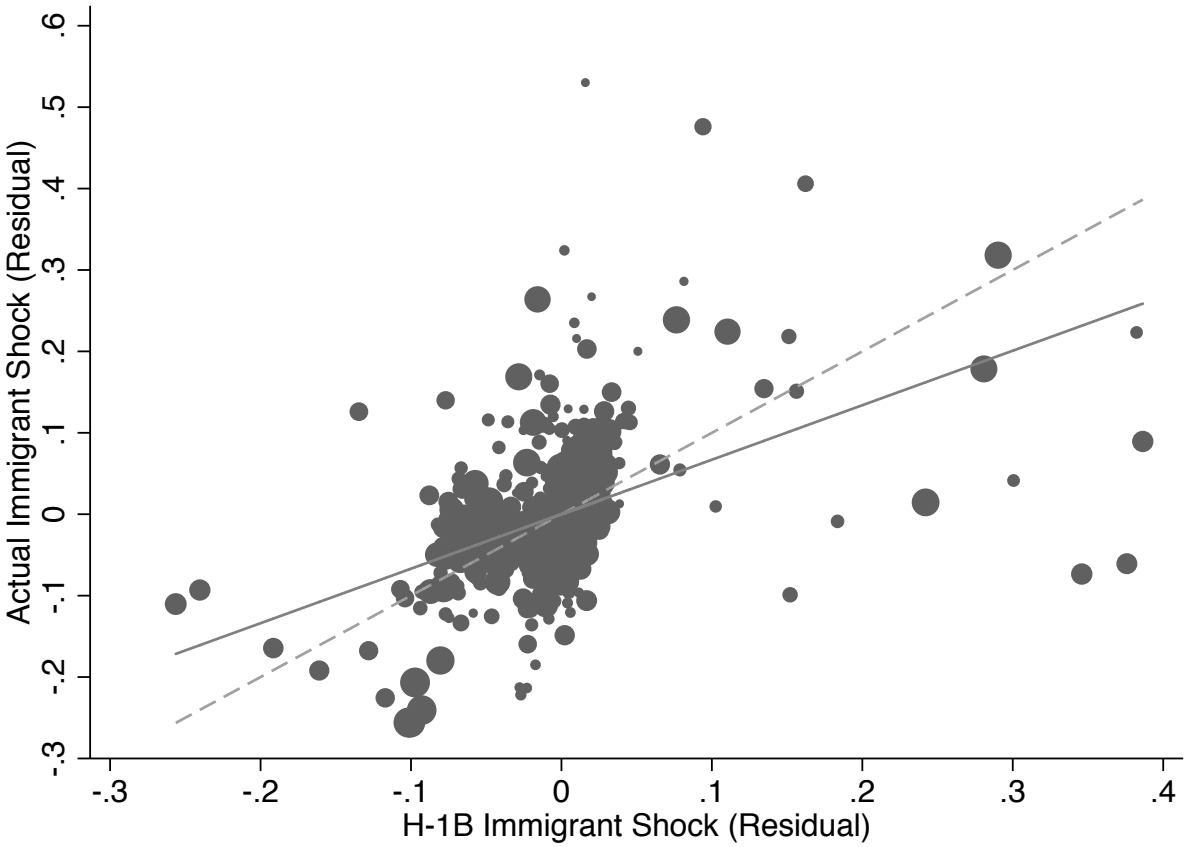
Notes: Based on author's calculations using the 1960-2000 decennial U.S. Census and the 2005-2015 American Community Surveys. The sample is all individuals aged 24-64 not living in group quarters. Individuals are coded as immigrants in 1960 if they were born outside of the United States and were not a U.S. citizen at birth and in 1970-2010 if they are naturalized citizen or not a citizen.

Figure 2: H-1B Immigrant Shock, 1990-2008



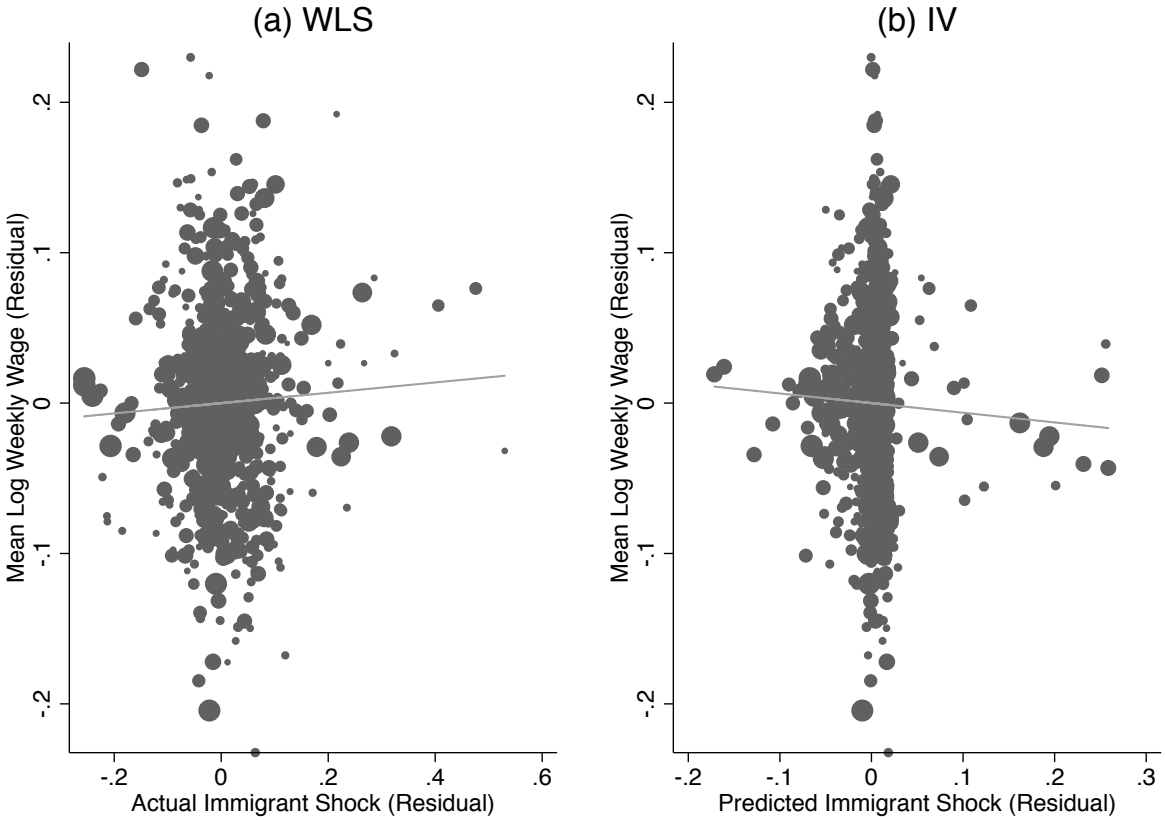
Notes: Based on author's calculations using the 2010-2012 American Community Survey (ACS) and the 2010-2015 Office of Foreign Labor Certification (OFLC) Disclosure Data for the H-1B Visa Program. The left panel plots the predicted number of immigrants to enter the United States each year due to the H-1B visa program. 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 occupation in the OFL and the joint distribution of majors and occupation in the ACS. The right panel plots the size of the immigrant shock and is the number of immigrants relative to the number of natives that entered the workforce in that year. See Table A-1 for the categorization of ACS degrees and Table A-3 for estimated shares.

Figure 3: Predicting the 2010 Immigrant Shock with Changes in H-1B 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-cohort cell for 40 college major groupings and 19 cohorts. The figure plots the estimated H-1B immigrant shock and the actual immigrant shock for each major-cohort cell net of major and cohort fixed effects on the horizontal axis and vertical axis, respectively. All major-cohort observations are weighted by the number of native observations in the cell. 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: OLS vs. Reduced-Form



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-cohort cell for 40 college major groupings and 19 cohorts. The figure in the left panel plots the actual immigrant shock and average log weekly earnings for each major-cohort cell net of major and cohort fixed effects on the horizontal axis and vertical axis, respectively. The figure in the right panel plots the predicted immigrant shock from the first-stage IV and average log weekly wages for each major-cohort cell net of major and cohort fixed effects on the horizontal axis and vertical axis, respectively. All major-cohort observations are weighted by the number of native observations in the cell. The solid line is the fitted line from weighted least squares regression.

Table 1: College Major Distribution 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 major groups according to Table A-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 combined shares of the five largest occupations in each row for all workers in the sample and only those that have completed a bachelor's degree. The share is then 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 Shock with Changes in H-1B Policy

	Immigrant Shock			H-1B Shock
	(1)	(2)	(3)	(4)
H-1B Immigrant Shock	0.669**	0.641**	0.439*	
	(0.198)	(0.192)	(0.176)	
Unemployment Rate		-10.53**	-10.02**	-1.538
		(3.294)	(3.172)	(0.955)
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	11.39	11.12	6.20	-
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. The dependent variable is the major-cohort immigrant shock calculated in 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. Specification (1) includes major and cohort fixed effects. Specification (2) 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 estimated in the monthly CPS into major-specific rates using the IPUMS 2010 harmonized occupation codes and the major-occupation distribution estimated in the 2010-2012 ACS. Specfication (3) adds major-specific linear cohort trends. In column (4), the dependent variable is the H-1B immigrant shock. Robust standard errors are in parentheses and are clustered by major. All regressions are weighted the number of native observations in a major-cohort 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 High-Skilled Immigration on Native Earnings

	WLS (1)	WLS (2)	WLS (3)	IV (4)	IV (5)	IV (6)
Panel A: Average Log Weekly Earmings						
Immigrant Shock	0.0343	0.0458	0.00937	-0.0641*	-0.0646*	-0.118*
	(0.0403)	(0.0460)	(0.0347)	(0.0306)	(0.0329)	(0.0503)
Unemployment Rate		1.165	0.319		-0.123	-1.042
		(1.772)	(1.107)		(1.723)	(1.401)
Panel B: Average Log Annual Earnings						
Immigrant Shock	0.0379	0.0490	0.00656	-0.0656*	-0.0664*	-0.125*
	(0.0417)	(0.0471)	(0.0349)	(0.0312)	(0.0332)	(0.0526)
Unemployment Rate		1.128	0.287		-0.218	-1.120
		(1.856)	(1.140)		(1.807)	(1.453)
Panel C: Average Log Hourly Earnings						
Immigrant Shock	0.0328	0.0472	0.0122	-0.0635*	-0.0629+	-0.127*
	(0.0378)	(0.0447)	(0.0328)	(0.0306)	(0.0324)	(0.0637)
Unemployment Rate		1.450	0.817		0.167	-0.667
		(1.601)	(1.166)		(1.533)	(1.528)
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	-	-	-	11.39	11.12	6.20
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 variables are major-cohort cell averages of log earnings using weekly earnings in Panel A, annual earnings in Panel B, and hourly earnings 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. Column (1)-(3) is estimated using weighted least squares. Columns (4)-(6) 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. Earnings are constructed by averaging over all natives. All regressions are weighted by the number of native observations in a major-cohort cell. Standard errors are reported in parentheses and are clustered at the major level.

** 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 by Group

	All	Men	Women	White	Black
	(1)	(2)	(3)	(4)	(5)
Panel A: Average Log Weekly Earmings					
Immigrant Shock	-0.118*	-0.168**	-0.0897	-0.114*	0.0936
	(0.0503)	(0.0465)	(0.103)	(0.0513)	(0.0958)
Unemployment Rate	-1.042	-0.141	-1.406	-0.914	1.233
	(1.401)	(1.561)	(2.103)	(1.314)	(2.495)
Panel B: Average Log Annual Earnings					
Immigrant Shock	-0.125*	-0.188**	-0.0952	-0.119*	0.0833
	(0.0526)	(0.0508)	(0.112)	(0.0524)	(0.0795)
Unemployment Rate	-1.120	-0.386	-1.629	-0.947	1.070
	(1.453)	(1.667)	(2.123)	(1.357)	(2.356)
Panel C: Average Log Hourly Earnings					
Immigrant Shock	-0.127*	-0.140*	-0.0452	-0.114*	0.0725
	(0.0637)	(0.0669)	(0.0951)	(0.0574)	(0.106)
Unemployment Rate	-0.667	0.322	-0.244	-0.689	1.937
	(1.528)	(1.589)	(1.929)	(1.354)	(2.382)
Major fixed effects	Yes	Yes	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes
Major-specific linear trend	Yes	Yes	Yes	Yes	Yes
F-statistic	6.20	6.20	6.20	6.20	6.20
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 major-cohort cell averages of log earnings using weekly earnings in Panel A, annual earnings in Panel B, and hourly earnings 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. Eanings are constructed by averaging over all natives in the listed subgroup. All regressions are weighted by the number of native observations in a major-cohort cell. Standard errors are reported in parentheses and are clustered at the major level.

** 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

	Employed		Full-Time		Hours (FTE)	
	WLS	IV	WLS	IV	WLS	IV
Dependent Variable Sample:	(1)	(2)	(3)	(4)	(5)	(6)
All Natives	0.00666	0.0785+	-0.0169	0.0228	-0.00913	0.00685
(N=760)	(0.0169)	(0.0460)	(0.0263)	(0.0382)	(0.0192)	(0.0281)
Native Men	-0.0142	0.0160	-0.0695+	-0.0931**	-0.0406	-0.0778**
(N=760)	(0.0216)	(0.0328)	(0.0400)	(0.0356)	(0.0286)	(0.0259)
Native Women	-0.00385	0.0455	-0.0201	-0.0357	-0.0200	-0.0416
(N=760)	(0.0192)	(0.0486)	(0.0323)	(0.0426)	(0.0225)	(0.0423)
White Natives	0.0188	0.0960+	-0.00474	0.0471	-0.00146	0.00950
(N=760)	(0.0173)	(0.0528)	(0.0244)	(0.0439)	(0.0176)	(0.0281)
Black Natives	-0.0248	0.0582	-0.0816+	-0.0461	-0.0632	0.0227
(N=758)	(0.0415)	(0.0665)	(0.0408)	(0.0690)	(0.0436)	(0.0764)
Major fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Major-specific linear trend	Yes	Yes	Yes	Yes	Yes	Yes

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 major-cohort cell averages of outcomes for the group of natives indicated at the the top of the column. 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. The instrument is the ratio of the estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. Columns (1), (3), and (5) are estimated using weighted least squares and columns (2), (4), and (6) are estimated using two-stage weighted least squares where the F-statistic from the first stage is 6.20. Regressions are weighted by the number of natives observations in a cell. Standard errors are reported in parentheses and are clustered at the major level.

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

Table 7: The Effect of High-Skilled Immigration on Native Occupational Earnings

	Own	Occupation Average 1990	Occupation Average 2010	Occupation Perc. Rank 1990	Occupation Perc. Rank 2010
	(1)	(2)	(3)	(4)	(5)
Panel A: Pooled Native Sample					
Immigrant Shock	-0.118*	-0.0792*	-0.0884+	-0.0619*	-0.0566*
	(0.0503)	(0.0385)	(0.0488)	(0.0277)	(0.0275)
Panel B: Male Native Sample					
Immigrant Shock	-0.168**	-0.0760+	-0.0918	-0.0579+	-0.0585+
	(0.0465)	(0.0434)	(0.0611)	(0.0297)	(0.0305)
Observations	760	760	760	760	760

Notes: Data are from the 1990 U.S. decennial census, 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. 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 cell averages of weekly earnings. In the remaining columns, individuals are assigned an occupation-specific wage measure: (2) average log weekly earnings in 1990, (3) average log weekly earnings from the 2010, (4) percentile rank of weekly earnings in 1990, and (5) percentile rank of weekly earnings in 2010. Wage measures from 1990 are assigned using the IPUMS 2010 harmonized occupation codes and from 2010 using the cleaned SOC occupation code used in constructing the instrument. Panel A averages the outcomes over all natives, whereas Panel B averages the outcomes using only the sample of native men. 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 estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. All specifications include major fixed effects, cohort fixed effects, and major-specific linear cohort trends, and control for the major-specific unemployment rate upon entering the U.S. labor market. Regressions are weighted by the number of native observations in a cell. Standard errors are reported in parentheses and are clustered at the major level.

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

Table 8: The Effect of High-Skilled Immigration on Native Tasks

	Interactive / Complex Cog. (Caines et al. 2016)	Interactive / Quantitative (Peri & Sparber 2011)	Leadership / Quantitative
	(1)	(2)	(3)
Panel A: Pooled Native Sample			
Immigrant Shock	0.0775**	0.0401*	0.0608*
	(0.0291)	(0.0170)	(0.0268)
Panel B: Male Native Sample			
Immigrant Shock	0.0454	0.0202	0.0651*
	(0.0318)	(0.0286)	(0.0323)
Observations	760	760	760

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, 2010-2015 Office of Foreign Labor Certification (OFLC) 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 variables are ratios of the percentile ranks of task-importance on current occupation. Column (1) compares interactive to complex cognitive tasks using classifications from Caines et al. (2016). Column (2) compares interactive to quantitative tasks using classifications Peri and Sparber (2011). Column (3) compares leadership to quantitative activities where the latter group is drawn from Peri and Sparber (2011). Panel A uses all natives, whereas Panel B uses only the sample of native men. 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 estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. All specifications include major fixed effects, cohort fixed effects, major-specific linear cohort trends, and control for the major-specific unemployment rate upon entering the U.S. labor market. Regressions are weighted by the number of native observations in a cell. Standard errors are reported in parentheses and are clustered at the major level.

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

Table 9: 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*	-0.210*		
	(0.0903)	(0.0902)		
Log Relative Efficiency Units			-0.194+	-0.186+
			(0.0971)	(0.0970)
Estimate of Elasticity of Substitution between STEM and Non-STEM	4.57	4.76	5.15	5.38
Panel B: Full-Time Wage Sample				
Log Relative Hours Worked	-0.311**	-0.306**		
	(0.0865)	(0.0888)		
Log Relative Efficiency Units			-0.276**	-0.271**
			(0.0950)	(0.0973)
Estimate of Elasticity of Substitution between STEM and Non-STEM	3.22	3.27	3.62	3.69
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 across the 2010-2012 and 2013-2015 surveys. Workers are grouped into STEM and non-STEM majors. The dependent variable is the difference in average log weekly earnings between STEM and non-STEM college majors. The explanatory variable is the difference in log labor supply between STEM and non-STEM college 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. Relative productivities are estimated by replicating Borjas (2014) and an elasticity of substitution across experience groups of 6.54 (1/0.153) is used. The coefficient on the explanatory variable represents the inverse of the elasticity of substitution between STEM and non-STEM and is reported below the results. Panel A constructs wages using the wage sample and Panel B uses full-time workers only. All specifications include state fixed effects and period fixed effects. Regressions are weighted by the number of observations in a cell (columns (1) and (3)) and inverse variance weight (columns (2) and (4)). 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 10: Simulated Increase in Non-STEM Wages Relative to STEM Wages Due to Immigration, 1990-2010

	College Major Shock (1)	STEM Occupation Shock (2)
Lower Bound: $\sigma = 2$	12.1%	7.3%
FT Wage Estimate: $\sigma = 3.5$	6.9%	4.2%
All Wage Estimate: $\sigma = 5$	4.8%	2.9%
Upper Bound: $\sigma = 6.7$	3.6%	2.2%

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 difference values of the elasticity of substitution between STEM and non-STEM workers. Each value represents the simulated increase in non-STEM wages relative to STEM wages due to the immigrant shock experienced between 1990 and 2010. See text for specifics on relative wage calculations.

A Appendix

Table A-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 A-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 A-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 A-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 A-4: Leadership Aggregate Classification - O*NET 21.1

Detailed O*NET Activity	O*NET Element
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. In this paper, I group six activities listed in the table into a Leadership index. The paper also uses other classifications. See the text of Caines et al. (2016) and Peri and Sparber (2011) for details.

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

	Average Earnings						Median Earnings	
	WLS	IV	WLS	IV	WLS	IV	WLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Immigrant shock	0.00937	-0.118*					0.0253	-0.0800*
	(0.0347)	(0.0503)					(0.0327)	(0.0347)
Immigrant shock (under 40)			0.0149	-0.131*				
			(0.0367)	(0.0557)				
Immigrant Share					0.0297	-0.231		
					(0.0780)	(0.212)		
Unemployment rate	0.319	-1.042	0.372	-1.131	0.333	-0.670	-0.699	-1.825+
	(1.107)	(1.401)	(1.105)	(1.441)	(1.011)	(1.494)	(1.213)	(1.069)
Major fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major-specific linear trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	-	6.20	-	7.60	-	44.29	-	6.20
Observations	760	760	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 major-cohort cell averages of log weekly earnings for columns (1)-(6) and the median log weekly earnings for columns (7)-(8). 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)-(2), the explanatory variable is the ratio of immigrants to natives in a major-cohort cell in the 2010-2012 ACS. In columns (3)-(4), immigrants who entered the U.S. after age 40 are removed from the explanatory variable. In columns (5)-(6), 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-specifc linear cohort trends. All regressions are weighted by the number of native observations in a major-cohort cell. Standard errors are reported in parentheses and are clustered at the major level.

** 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 Immigrant on Native Weekly Earnings, Alternative Weights

	All Workers		Full-Time Workers	
	Pooled	Men	Pooled	Men
Weights used:	(1)	(2)	(3)	(4)
Unweighted	-0.0632	-0.153*	-0.0282	-0.108
	(0.0618)	(0.0661)	(0.0662)	(0.0663)
Number of native observations in major-cohort cell	-0.118*	-0.168**	-0.0871+	-0.133**
	(0.0503)	(0.0465)	(0.0488)	(0.0492)
Number of native observations used to average wages	-0.119*	-0.195**	-0.0975*	-0.157**
	(0.0503)	(0.0413)	(0.0467)	(0.0426)
Sample variance of average wages	-0.115*	-0.200**	-0.0969*	-0.166**
	(0.0483)	(0.0429)	(0.0433)	(0.0444)

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. Each row is weighted by the weight listed in the left column. Standard errors are reported in parentheses and are clustered at the major level.

** 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 Immigrant on Native Tasks

	Pooled Natives		Male Natives	
	Beta	Std. Error	Beta	Std. Error
Task:	(1)	(2)	(3)	(4)
Analytical or Quantitative Tasks				
Analyze Data or Information	-0.0506*	(0.0246)	-0.0523	(0.0341)
Deductive Reasoning	-0.0532*	(0.0236)	-0.0520	(0.0316)
Inductive Reasoning	-0.0558+	(0.0288)	-0.0541	(0.0391)
Estimating Quantifiable Characteristics	0.0221	(0.0301)	0.0432	(0.0290)
Mathematical Reasoning	-0.0160	(0.0205)	-0.0221	(0.0220)
Interactive or Communication Tasks				
Resolving Conflicts / Negotiating	0.0208	(0.0263)	0.00299	(0.0213)
Communicating Within Organization	0.0196	(0.0277)	0.0318	(0.0324)
Communicating Outside Organization	0.00387	(0.0229)	-0.00458	(0.0288)
Oral Comprehension	-0.0334+	(0.0174)	-0.0325	(0.0259)
Written Comprehension	-0.0253	(0.0180)	-0.0288	(0.0253)
Written Expression	-0.0576**	(0.0220)	-0.0579+	(0.0306)
Oral Expression	-0.0584**	(0.0214)	-0.0635*	(0.0293)
Leadership / Management:				
Coordinate Others' Work Activities	-0.00544	(0.0252)	-0.00403	(0.0305)
Develop and Build Teams	0.00563	(0.0280)	0.0183	(0.0335)
Training and Teaching Others	-0.0318+	(0.0177)	-0.0141	(0.0267)
Guide, Direct, and Motivate Subordinates	0.0124	(0.0336)	0.0285	(0.0381)
Coach and Develop Others	-0.0185	(0.0221)	-0.00744	(0.0272)
Staff Organizational Units	0.0498	(0.0479)	0.0435	(0.0461)

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, 2010-2015 Office of Foreign Labor Certification (OFLC) 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 variables are percentile ranks of the importance of groups of tasks based on current occupation. Tasks are grouped by their correspondence to the Peri and Sparber (2011) index. The last group are tasks related to leadership or management. Column 1 averages the outcomes over all natives, whereas column 3 averages the outcomes using only the sample of native men. 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 estimated H-1B immigrants to the number of natives in the 2010-2012 ACS. All specifications include major fixed effects, cohort fixed effects, and major-specific linear cohort trends, and control for the major-specific unemployment rate upon entering the U.S. labor market. Regressions are weighted by the number of native observations in a cell. Standard errors are reported in parentheses and are clustered at the major level.

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