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

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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 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 major-experience groups with relatively more immigrants have lower wages on average. Specifically, I define the immigrant shock as the immigrant-native ratio in a major-experience group. Computer Science majors experienced the largest increase in this variable throughout the 1990s. My results suggest that the 50 percentage point increase in the immigrant shock between 1990 and 2000 decreased the relative wages of the native Computer Scientists that graduated in 2000 by 6 percent. 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.

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 specific 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 group. 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 an 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

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 elds, 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 e ects of immigration if immigrants have di erent majors than natives. If immigrants have the same college major distribution as natives, the relative wages of di erent major groups would not change. However, they do not have the same distribution. Table 1 shows the distribution of college majors from 2010-2012 in the United States separately for natives (col. 1) and immigrants (col. 2). Strikingly, immigrants are nearly twice as likely to have studied a STEM eld, 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 eld, immigrants are overrepresented in Business and Healthcare and underrepresented in the Social Sciences and Education elds.

To demonstrate that college major better characterizes distinct factors of production, I show that occupations become more concentrated as the de nition of skill group becomes more tightly de ned. Occupations are based o a worker's three-digit Standard Occupational Classi cation (SOC) code and the sample 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 ve 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 de ned skill group are more substitutable. Indeed, the data demonstrate this pattern. Twenty-two percent of all workers work in the ve 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 nd an average share of 49 percent. Within the detailed major groups, occupations become more -274ationauie (Wi(is)-349-27(963l8-352(th3 to change occupations in order for the groups to have the same distribution.

Panel B of Table 2 presents the index of similarity between di erent groups. The rst 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 nal row compares natives to immigrants within each major. As workers begin to be grouped into more tightly de ned 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 majorstage over simply grouping by
occupation. It would not be di cult to categorize occupations into a subset of skill groups. However, thish Theretialesond
immigration by switching occupation (e.g., Peri and Sparber, 2009, 2011), which makes it di cult to estimate the e ect of immigration on wages. Conversely, college major is largely a predetermined

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]

$$Y = A\left[\alpha K^{\rho} + (1-\alpha) L^{\rho}\right]^{1/\rho}; \tag{2}$$

where A is total factor productivity and the elasticity of substitution between capital and labor is defined as $\sigma_{KL} = 1/(1-\rho)$ and $\rho < 1$.[8] The labor aggregate is made up of two different inputs, efficiency units supplied by low-skill 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:

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

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-skill and high-skill workers is defined as $\sigma_E = 1/(1-\delta)$ and $\delta < 1$.

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

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

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 $_{M} = 1{=}(1 \quad)$ and $\; < 1$.

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

$$L_m = \left[\sum_{x} \quad _{mx} (L_{mx}) \quad \right]^{1=} ; \qquad (5)$$

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

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 < 1, 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 relative productivity $_{mx}$ is additively separable into a major-speci c component $_m$, an experience-speci c component $_x$, and a stochastic component $_{mx}$ with mean zero such that $\log _{mx} = \ _m + \ _x + \ _{mx}$.[11] Taking the log of Equation 6 and grouping like terms provides the following estimating equation:

$$\log w_{mx} = \quad + \ _m + \ _x \ \frac{1}{\ _X} \log L_{mx} + \ _{mx}; \qquad (8)$$

where $= \log (1 \quad) Y^{1} \ L \ ^{1} \ _S L^{1} \ (L^S) \ ^{1}$ and $_m = \log \ _m (L^S)^{1} \ L_m \ + \ _m$. 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-speci c characteristics. Identifying the parameter $_X$ requires an exogenous shifter of the labor supply. Immigrants are commonly used. Because data ires 9J/F2hBecau7 11.9552 Tf 6..97 0.79x[07ction27(t Td [0717.927 Tda)

$_{mx} = \ + \ _m + \ _x \ 1$

given parameters of the model, one can simulate relative wage e ects at those higher levels. The e ect on wages from a generalized supply-shift from immigration are characterized in Borjas (2014).

that cannot be detected in this framework. It could be that immigrants bring ideas or generate 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

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.

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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 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 speci c 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 rst variable compares the importance of interactive tasks relative to complex cognitive tasks and follows the classi cation used by Caines et al. (2016). The second variable compares the importance of interactive tasks and skills relative to quantitative tasks and skills as de ned 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 de ne 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 de nition 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). A 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:

$$\ln w^{N}_{mx} = \quad_{m} + \quad_{x} + x \quad_{m} + \quad p_{mx} + \quad_{mx} \tag{14}$$

where $\ln w^{N}_{mx}$ is the average log weekly earnings of natives with college major m in experience cohort x, $\ _m$ is a set of major fixed effects, which controls for characteristics of a college major common to all cohorts, and $\ _x$ non-parametrically control for the wage-experience profile of all college-educated workers. Additionally, major-specific linear cohort trends, $x \ \ _m$, 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, , 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 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 a ected by policy changes. The instrument is de ned by $p^{IV}_{mx} = \hat{M}_{mx} = N_{mx}$ 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 rst-stage is given by

$$p_{mx} = \quad_m + \quad_x + x \quad_m + \quad p^{IV}_{mx} + u_{mx} \tag{15}$$

and the second-stage is given by Equation 14. Identi cation of the second stage requires a strong correlation between the predicted H-1B immigrant shock, p^{IV}_{mx}, and the actual immigrant shock, p_{mx}. Figure 3 plots the rst-stage relationship between the instrumented immigrant shock, using changes in the H-1B program, and the actual immigrant shock, net of major and cohort xed e ects. The dashed line in this gure represents the forty- ve degree line. The solid line demonstrates the positive relationship between the predicted and actual immigrant shocks. Results from various rst-stage speci cations are presented in Table 3. The base speci cation (col. 1) begins by controlling for major and cohort xed e ects. 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-speci c unemployment rate at labor market entry, which only slightly changes the estimate. Finally, column 3 adds major-speci c linear cohort trends. The rst-stage coe cient decreases in magnitude and loses some signi cance. However, the estimate is still signi cant at the 5 percent level (F-stat=6.20). The weaker signi cance in column 3 introduces a concern about weak instruments. However, Bound et a -17 a ofalightly in 2tv1c356

3.2.2 Estimation Issues

The exclusion restriction relies on two assumptions: (1) the predicted H-1B immigrant shock, and the instrument. It is encouraging that the e ect of this control on the instrument is insigni cant.

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 di erences in cell-level variance. Indeed, estimates become more precise with weights con rming 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 xed e ects. 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 but statistically insigni cant. Controlling for the major-speci c unemployment rate increases the point estimate (col. 2) and additionally controlling for major-speci c linear cohort trends reduces the coe cient 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 signi cant at the 1 percent level. Column 6 presents results that control for both the unemployment rate and linear trends. The estimate is -0.118 and is signi cant at the 5 percent level.

Section 3.2 highlights that this is a relative wage e ect 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 eld. The immigrant shock for Computer Science majors increased from about 0.35 in the early 1990s to about 0.85 at the peak of the H-1B cap in the late 1990s and early 2000s, decreaseing relative wages by about 6 percent.

Results are robust to di erent measures of group-speci c earnings. The remainder of Table 4 presents estimates using di erent 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 speci cations. 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 insigni cant. 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 e ect 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 e ects by focusing on the average log weekly earnings of speci c native subgroups. I consider the following subgroups: native men, native women, white natives, and black natives. The e ect is strongest and most precisely estimated among native men. The point estimate is -0.168 and is signi cant 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

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

5 Simulation

While the previous section documents a negative causal relationship between immigration and wages, the question of how high-skill immigration a ected the wages of workers across di erent 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.

skill 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 $_X$ 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 2 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 $_M$.

I estimate $_M$ 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 speci cations include state and period xed e ects 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 e ciency 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 di erent 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 e ciency units.

The estimated value of $_M$ 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 di erent 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 E ects

With values of $_M$ 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 $_X$.

2003; Ottaviano and Peri, 2012) or looked at earnings and employment e ects on native STEM graduates only (Ransom and Winters, 2016). I implement an estimation strategy that allows for

References

Altonji, Jesph G., Peter Arcidiacono, and Arnaud Maurel , \The Analysis of Field Choice in College and Graduate School: Determinants and Wage E ects," NBER Working Paper 21655, October 2015.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger , \Computing Inequality: Have Computers Changed the Labor Market," The Quarterly Journal of Economics, November 1998, 113 (4), 1169{1213.

Blom, Erica, Brian C. Cadena, and Benjamin J. Keys , \Investment over the Business Cycle: Insights from College Major Choice," IZA Discussion Paper No. 9167, July 2015.

Borjas, George J. , \The Labor Demand Curve is Downward Sloping: Reexmaining the Impact of Immigration on the Labor Market," Quarterly Journal of Economics, November 2003, 118 (4), 1335{1374.

—, Immigration Economics, Harvard University Press, 2014.

— and Kirk B. Doran , \The Collapse of the Soviet Union and the Productivity of American Mathematicians," The Quarterly Journal of Economics, August 2012, 127 (3), 1143{1203.

— and Lawrence F. Katz , \The Evolution of the Mexican-Born Workforce in the United States," in George J. Borjas, ed., Mexican Immigration to the United States, University of Chicago Press, 2007, chapter 1, pp. 13{56.

—, Je rey Grogger, and Gordon H. Hanson , \Comment: On Estimating Elasticities of Substitution," Journal of the European Economic Association, February 2012, 10 (1), 198{223.

Bound, John, David Jaeger, and Regina M. Baker , \Problems with Instrumental Variabels Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak," Journal of the American Statistical Association, June 1995, 90 (430), 443{450.

—, Gaurav Khanna, and Nicolas Morales , \Understanding the Economic Impact of the H-1B Program on the U.S.," NBER Working Paper 23153, February 2017.

Caines, Colin, Florian Ho mann, and Gueorgui Kambourov , \Complex Occupations and Labor Market Polarization: An Empirical Investigation," Working Paper, March 2016.

Card, David , \Immigration and Inequality," American Economic Review: Papers and Proceedings, May 2009, 99 (2), 1{21.

— and Thomas Lemieux , \Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis," The Quarterly Journal of Economics, May 2001, 116 (2), 705{746.

Doran, Kirk B., Alexander Gelber, and Adam Isen , \The E ects of High-Skilled Immigration Policy on Firms: Evidence from Visa Lotteries," Working Paper, February 2016.

Dustmann, Christian, Uta Schönberg, and Jan Stuhler , \The Impact of Immigration: Why Do Studies Reach Such Di erent Results?," Journal of Economic Perspectives, 2016, 30 (4), 31{56.

Federman, Maya N., David E. Harrington, and Kathy J. Krynski

Hunt, Jennifer, \Which Immigrants are Most Innovative and Entrepreneurial? Distinctions by Entry Visa," *Journal of Labor Economics*, July 2011, *29* (3), 417{457.

—, \How Restricted is the Job Mobility of Skilled Temporary Work Visa Holders?," *NBER Working Paper 23529*, June 2017.

— and Marjolaine Gauthier-Loiselle, \How Much Does Immigration Boost Innovation?," *American Economic Journal: Macroeconomics*, April 2010, *2* (2), 31{56.

Kaestner, Robert and Neeraj Kaushal, \E ect of Immigrant Nurses on Labor Market Outcomes of US Nurses," *Journal of Urban Economics*, 2012, *71*, 219{229.

Katz, Lawrence and David Murphy, \Changes in Relative Wages: Supply and Demand Factors," *Quarterly Journal of Economics*, February 1992, *107* (1), 35{78.

Kerr, William R. and William F. Lincoln, \The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention," *Journal of Labor Economics*, July 2010 (3), 473{508(Ec)51(onomics)]TJ/F8 9H 0 Td [289

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st, July 2011, Highly Educated Immigrants and Native Occup(ation)1nal Choice n,"
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and

Rothwell, Jonathan, José Lobo, Deborah Strumsky, and Mark Muro, "Patenting Prosperity: Invention and Economic Performance in the United States and its Metropolitan Areas," Brookings Institute Metropolitan Policy Program, February 2013.

Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek, *Integrated Public Use Microdata Series: Version 6.0 [dataset]*, Minneapolis: University of Minnesota, 2015.

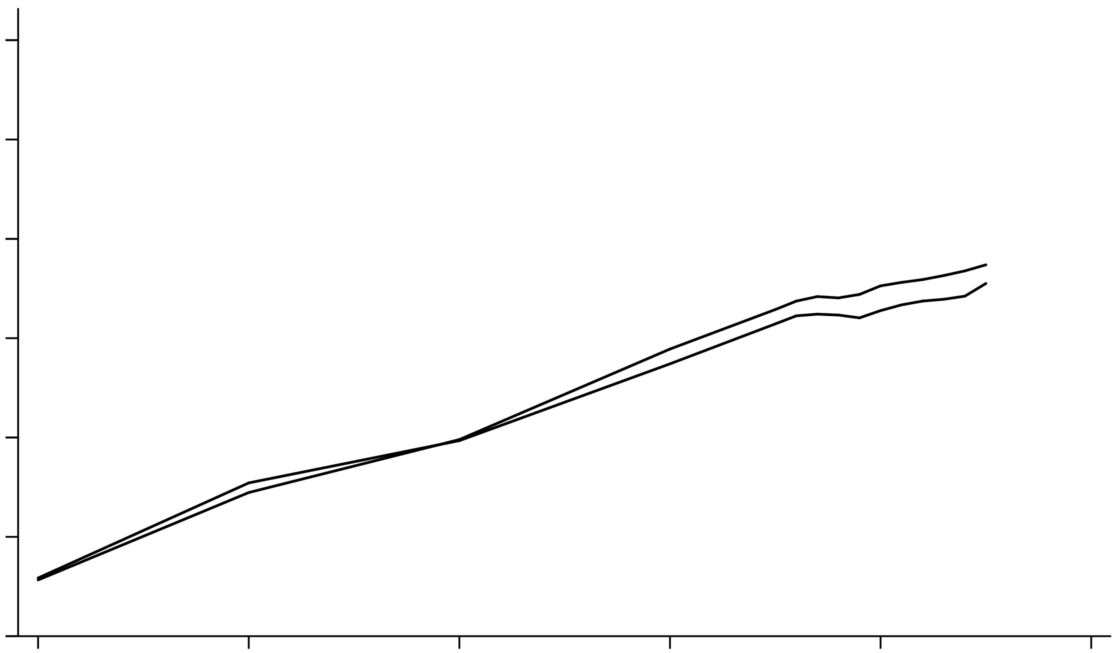
Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge, "What Are We Weighting For?," *Journal of Human Resources*, March 2015, *50* (2), 301–316.

Sparber, Chad, "Choosing Skilled Foreign-Born Workers: Evaluating Alternative Methods for Allocating H-1B Work Permits," *Industrial Relations*, Forthcoming.

Spreen, Thomas Luke, "Recent College Graduates in the U.S. Labor Force: Data from the Current Population Survey," *Monthly Labor Review*, February 2013, pp. 3–13.

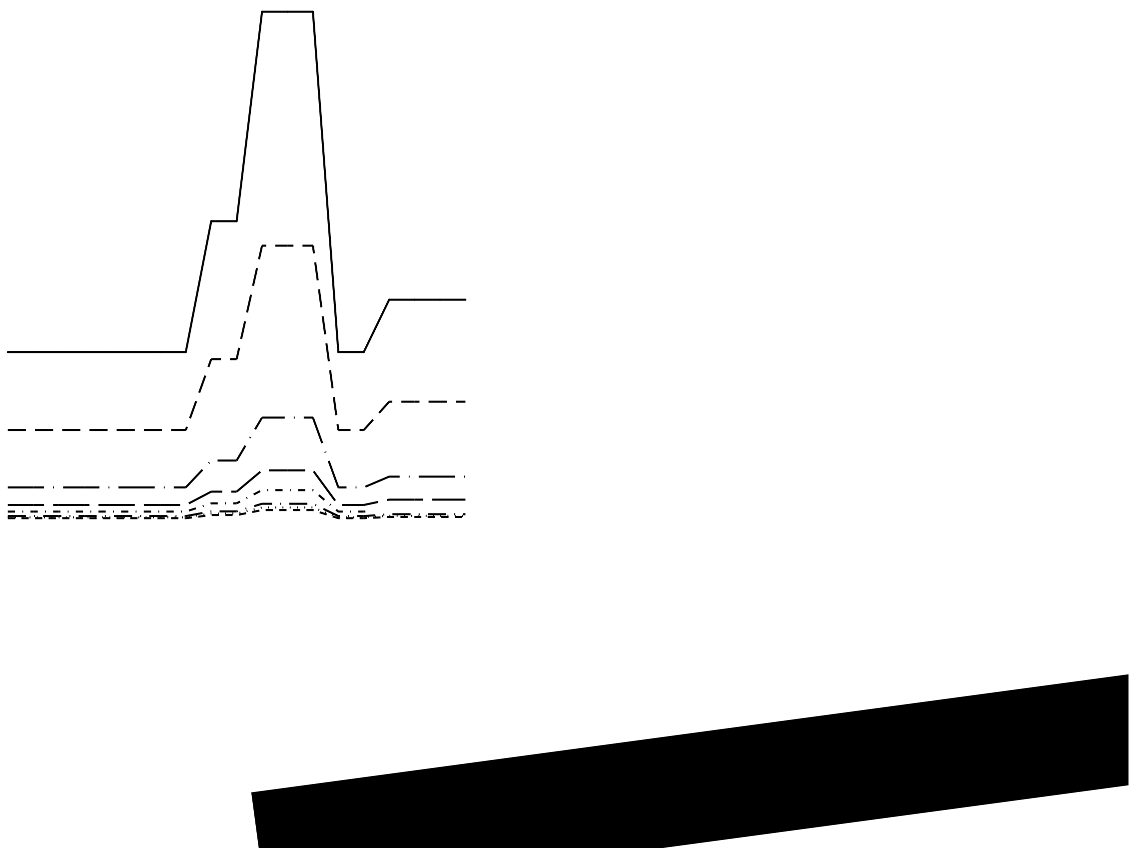
Winters, John V., "Foreign and Native-Born STEM Graduates and Innovation Intensity in the United States," IZA Discussion Paper No. 8575, October 2014.

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



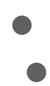
Notes: Based on author's calculations using the 1960-2000 decennial U.S. Census and the 2005-2015 American Community Surveys. The sample is all individuals aged 24-64 not living in group quarters. Individuals are coded as immigrants in 1960 if they were born outside of the United States and were not 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 O ce of Foreign Labor Certi cation (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 O ce of Foreign Labor Certi cation (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 gure plots the estimated H-1B immigrant shock and the actual immigrant shock for each major-cohort cell net of major and cohort xed e ects 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 tted line from weighted least squares regression.

Figure 4: The E ect of High-Skill 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 O ce of Foreign Labor Certi cation (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 gure in the left panel plots the actual immigrant shock and average log weekly earnings for each major-cohort cell net of major and cohort xed e ects on the horizontal axis and vertical axis, respectively. The gure in the right panel plots the predicted immigrant shock from the rst-stage IV and average log weekly wages for each major-cohort cell net of major and cohort xed e ects on the horizontal axis and vertical axis, respectively. All major-cohort observations are weighted bymajthecer-399(obf9(jthe)tiv)20(ce]TJ 0 -9.46

Table 1: College Major Distribution by Nativity Status

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 rst degree reported by the respondent and are classi ed into seven broad major groups according to Table A-1.

Table 2: Occupational Distributions by Education Group

Table 3: Predicting the 2010 Immigrant Shock with Changes in H-1B Policy

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 O ce of Foreign Labor Certi cation (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. Speci cation (1) includes major and cohort xed e ects. Speci cation (2) controls for the major-speci c unemployment rate upon entry into the U.S. labor market. The unemployment rate is calculated by converting occupation-speci c unemployment rates estimated in the monthly CPS into major-speci c rates using the IPUMS 2010 harmonized occupation codes and the major-occupation distribution estimated in the 2010-2012 ACS. Spec cation (3) adds major-speci c 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 coe cient on the H-1B immigrant shock is zero.

** Signi cant at the 1 percent level
* Signi cant at the 5 percent level
+ Signi cant at the 10 percent level

Table 4: The E ect of High-Skill Immigration on Native Earnings

Panel A: Average Log Weekly Earmings

Panel B: Average Log Annual Earnings

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 O ce of Foreign Labor Certi cation 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

Table 5: The E ect of High-Skill 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)			

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, and 2010-2015 O ce of Foreign Labor Certi cation 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.

** Signi cant at the 1 percent level

* Signi cant at the 5 percent level

+ Signi cant at the 10 percent level

Table 6: The Effect of High School Immigration on Native Employment

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 E ect of High School Immigration on Native Earnings

(0.0503

	[illegible]Own	Occu[illegible]tion Ave[illegible]ge 19[illegible]	Occupat[illegible] Avera[illegible] [illegible]2010[illegible]	Occu[illegible]ation Perc. [illegible]ank 19[illegible]	[illegible]ccupa[illegible]n Perc. Ra[illegible]k [illegible]
	[illegible](1)	(2)	[illegible]3)	(4[illegible]	(5)
Pa[illegible]el A: P[illegible]led Na[illegible]e Sample					
Im[illegible]grant Sh[illegible]	-0.1[illegible]	-0.079[illegible]	[illegible]0.0884+	[illegible]0619*	[illegible]6*
	(0.0503)	(0.0385)	(0.0488)	(0.0277)	(0.0275)
Panel B: Male Native Sample					
Immigrant Shock	-0.168**	-0.0760+	-0.09q 51 459 488 17 re W sc q 1		

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 O ce of Foreign Labor Certi cation (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-speci c 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 speci cations include major xed e ects, cohort xed e ects, and major-speci c linear cohort trends, and control for the major-speci c unemployment rate upon entering the U.S. labor market. Regressions are weragεenterag mat

Table 8: The E ect of High School Immigration on Native Tasks

Panel A: Pooled Native Sample

Panel B: Male Native Sample

Notes: Data are from the 2010-2012 American Community Survey, the 1990-2008 monthly Current Population Survey, 2010-2015 O ce of Foreign Labor Certi cation (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

Table 9: Estimates of the Elasticity of Substitution between STEM and Non-STEM Majors

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 di erence in average log weekly earnings between STEM and non-STEM college majors. The explanatory variable is the di erence 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 e ciency 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 coe cient 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 speci cations include state xed e ects and period xed e ects. 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.

** Signi cant at the 1 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: ! = 2	12.1%	7.3%
FT Wage Estimate: ! = 3.5	6.9%	4.2%
All Wage Estimate: ! = 5	4.8%	2.9%
Upper Bound: ! = 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 di erent wage simulation based on di erence 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 speci cs on relative wage calculations.

A Appendix

Table A-1: College Major Classi cation

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, 24
		2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 24
		2499, 2500, 2501, 2502, 2503, 2504, 2599, 3801, 5008
	Life Sciences	1103, 1104, 1105, 1106, 1301, 3600, 3601, 3602, 3603, 36
		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 classi cations: 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)

Notes: Based on author's calculations using the 2010-2012 American Community Survey and 2010-2015 O ce of Foreign Labor Certi cation Disclosure Data for the H-1B Visa Program. To compare occupations across datasets, I rst construct a crosswalk between the SOC codes found in the H-1B data and the ACS le. Each panel represents a di erent occupation. The share of the occupation in the H-1B data is calculated all applications from 2010-2015. The occupation-speci c 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

Notes: Based on author's calculations using the 2010-2012 American Community Survey and 2010-2015 O ce of Foreign Labor Certi cation 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 speci c 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 Classi cation - 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

Table A-5: The E ect of High-Skill 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 O ce of Foreign Labor Certi cation 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.

Table A-6: The E ect of High-Skill 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 O ce of Foreign Labor Certi cation (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.

** Signi cant at the 1 percent level
* Signi cant at the 5 percent level
+ Signi cant at the 10 percent level

Table A-7: The Effect of High-Skill 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)
Train and Teach 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