An Inquiry on the Impact of Highly-skilled STEM Immigration on the U.S. Economy

Christian Gunadi
Department of Economics
University of California, Riverside

September 30, 2018

Job Market Paper

Abstract

This article estimates the potential economic benefits of STEM immigration and examines the impact of highly skilled STEM immigration on the wage structure in the United States. Considering that foreign-born share of STEM workers has been increasing rapidly in recent years, there are new interests in examining the extent to which labor market outcomes of natives – and immigrants alike – are affected by this supply inflow. The analysis yields a few main findings. First, U.S. and foreign-born STEM workers with similar skills have a high but finite elasticity of substitution (~18), implying that the adverse impact of STEM immigration would be more concentrated among immigrant STEM workers themselves. Second, 2000-2015 foreign STEM labor supply shock increases the average wage of preexisting U.S.-born STEM workers by 4.67 percent. This finding, however, masks a distributional consequence of the shock as native STEM workers with higher educational attainment experience lower wage gains. Third, the economic benefit for native workers from 2000-2015 foreign STEM supply shock is approximately 103 billion USD or 1.03% of U.S. GDP in 1999. Almost all of this benefit comes from the productivity spillovers associated with high-skilled STEM immigration that increase the productivity and wages of U.S.-born workers. Finally, the average wage of U.S.-born STEM workers would have been approximately 1 percentage point higher in the absence of the H-1B Visa Reform Act of 2004.

JEL Classification: J31, J61, J68

Keywords: Immigration, Wages, STEM, highly skilled labor

E-mail address: christian.gunadi@email.ucr.edu. I would like to thank Joseph Cummins, Michael Bates, Steven Helfand, Giovanni Peri, all participants in All California Labor Conference 2017 and Applied Economics Seminar at UC Riverside for their comments and suggestions. All mistakes are my own.

1 Introduction

Over the past decades, the United States has experienced a large inflow of highly skilled STEM workers. Between 2000 and 2015, the foreign-born share of STEM workers increased from approximately 16% to 24% (Figure 1). In the face of this trend, there are new interests in examining the extent to which labor market outcomes of natives – and immigrants alike – are affected by this supply inflow. Despite a large number of studies on the effect of overall immigration (e.g., Card, 1990; Borjas, 2003; Ottaviano and Peri, 2012), very little is understood about how high-skilled STEM immigration affects the U.S. labor market. In this paper, I attempt to present new insights to several key issues regarding high-skilled STEM immigration in the United States.

Recently, there is an intense debate in the U.S. on whether foreign STEM workers displace or complement U.S.-born STEM workers. This issue was raised by the emergence of cases claiming that U.S. firms were abusing high-skilled H-1B visas to bring foreign STEM workers to do the work of native STEM workers for less money.[1] Although it might be hard to ascertain the intention of firms when they hire foreign-born STEM workers, it is possible to shed light on this issue by examining the degree of substitutability between similarly skilled U.S.- and foreign-born STEM workers. If these workers are imperfect substitutes, then the influx of foreign STEM workers would result in a higher competition among immigrants themselves, mitigating its adverse impact on the wage and employment outcomes of U.S.-born STEM workers. I begin my analysis by outlining the theoretical framework to examine this issue. Using the framework, I found that similarly skilled U.S.- and foreign-born STEM workers are imperfect substitutes with an elasticity

[1]A recent high profile case includes Disney lawsuit in which former workers claimed that the company used H-1B visas to displace American workers. Although this lawsuit was eventually dismissed, the case received national attention and spurred congressional hearing on the impact of high-skilled immigration on U.S. workers.

of substitution of approximately 18. This finding suggests that although displacement may occur, it is relatively hard for U.S. firms to fully replace its native STEM workers with their foreign-born counterparts.

I continue the analysis by examining how much the returns to skills within the STEM fields are affected by STEM immigration. When foreign-born STEM workers enter the U.S. labor market, they are heterogeneous in terms of their age/experience and educational attainment. Many studies (e.g., Kerr and Lincoln, 2010; Peri et al., 2015), however, have overlooked this heterogeneity in their analysis. To see why this is important, one can see that the changes of foreign STEM workers across skill groups between 2000 and 2015 had disproportionately increased the supply of relatively older STEM workers with bachelor and post-graduate degrees (Table 1).[2] The differences in the magnitude of the supply shift across skill groups within STEM fields implies that if the preexisting workforce in 2000 experiences immigrants' supply shock that is as large as the changes observed from 2000 to 2015, the wage of older STEM workers with higher educational attainment would be more adversely affected relative to the wage of younger STEM workers with lower educational achievement. The results of the analysis suggest that although 2000-2015 foreign STEM labor supply shock increased the wage of preexisting U.S.-born STEM workers by 4.67 percent, native STEM workers with higher educational attainment experienced lower wage gains. I do not find that the wage of older U.S.-born STEM workers to be much more adversely affected compared to younger native STEM workers. This is because the degree of substitution between young and older workers in the STEM sector is relatively high.

[2]It should be noted that these changes in the supply across skill groups from 2000 to 2015 are caused by both net migration and the aging of immigrants who arrived at a younger age. Therefore, the wage effect estimates presented in this paper is a 'simulated' wage effect to see how much the wage of the preexisting workforce in 2000 change if they experienced the supply shift in the magnitude observed in Table 1. This way of estimating the wage effect is consistent with previous works such as Borjas (2003), Ottaviano and Peri (2012), and Manacorda et al. (2012).

Using the resulting wage effect estimates, it is possible to quantify the economic benefit of 2000-2015 foreign STEM labor supply shock that accrues to U.S.-born workers. A simple back of the envelope cost-benefit calculation suggests that the economic benefit for native workers is approximately 103 billion USD or 1.03% of U.S. GDP in 1999. It is worth noting that almost all of the benefit can be attributed to productivity spillovers generated by the influx of highly skilled STEM workers. In the absence of this productivity spillovers, the economic benefit accrues for native workers is approximately only 1.64 billion USD or 0.02% of U.S. GDP in 1999. These results imply that the main benefit of STEM immigration comes largely from the generation of ideas associated with high-skilled STEM immigration which promotes the development of new technologies that increase the productivity and wages of U.S.-born workers. In the absence of these productivity spillovers, the economic impact of STEM immigration on the U.S. economy would likely be relatively small.

Finally, I estimated the effect of the H-1B Visa Reform Act of 2004, which reduced the annual new issuances of H-1B visa from 195,000 to 85,000 starting in the fiscal year 2004, by considering how much the wage effect changes when I took into account all the additional immigrant STEM workers who would enter the U.S. by the end of 2015 in the absence of the reform. The counterfactual simulation suggests that the wage of U.S.-born STEM workers would have been higher by approximately 1 percentage point in the absence of the reform. Furthermore, the economic benefit that accrues to native workers would have been approximately 21.87 billion USD higher. This result suggests that policies that reduce the flow of highly-skilled STEM foreign worker into the country may have an adverse effect on the wages of native workers by stifling technological progress and innovations.

This paper contributes to the emerging literature that tries to examine the impact of high-skilled immigration on U.S. workers. Traditionally, the economics literature has focused on immigration in the lower-skilled groups (e.g., Card, 1990; Borjas, 2017; Peri and Yasenov, 2018). However, an increasingly larger share of foreign-born in the total STEM workers pool spurs interests in examining the economic impact of high-skilled immigration. Recent research on the topic has focused on finding evidence of positive spillover effects of high-skilled immigration (Hunt and Gauthier-Loiselle, 2010; Borjas and Doran, 2012; Moser et al., 2014), while only a few studies tried to examine how the wages of U.S.-born STEM workers are affected by STEM immigration (Kerr and Lincoln, 2010; Peri et al., 2015). This paper extends this literature by examining the degree of substitutability of similarly skilled U.S.- and foreign-born STEM workers, investigating how much the return to skills within the STEM fields are affected by STEM immigration, and quantifying the potential economic benefit of STEM immigration that accrues to U.S.-born workers.

This paper also contributes to the literature that examines the impact of immigration policy on the labor market outcomes of natives. Recent studies have mainly focused on policies aimed toward low-skilled undocumented immigrants, examining the difference in the natives' outcomes between states that adopt the policy and those that do not (e.g., Bohn et al., 2015; Orrenius and Zavodny, 2015). Policies aimed at high-skilled immigrants such as the H-1B Visa Reform Act of 2004, however, are much harder to assess as it was implemented at the national level. The structural approach in this paper circumvents the problem in assessing policies that were implemented at the national level and allowed me to estimate the impact of the H-1B Visa Reform Act of 2004.

The rest of the paper is constructed as follows. Section 2 describes the theoretical framework. Section 3 describes the data used in the analysis. Section 4 and 5 present the estimation of the parameters used to simulate the wage effect of STEM immigration.

Section 6 documents the results of the analysis. Section 7 concludes.

2 Theoretical Framework

In this section, I present a nested CES framework to estimate the impact of STEM immigration on the wage structure. The model is similar to Peri et al. (2015). However, I extend the model directly by considering that STEM workers may provide different inputs into aggregate production function depending on their skill (education-age) and place of their birth (foreign or U.S. born).

Suppose that the aggregate output at time t is produced by the contribution of skilled and unskilled workers:[3]

$$Y_t = \left\{ A(S_t) \Big[\beta(S_t) H_t^{\rho} + (1 - \beta(S_t)) L_t^{\rho} \Big] \right\}^{\frac{1}{\rho}} \tag{1}$$

where H and L represent skilled and unskilled labor, respectively. $A(S_t)$ represents skill-neutral technology parameter, and $\beta(S_t) \in [0, 1]$ is the relative productivity of high-skilled labor. It follows that an increase in β represents a technological change that favors skilled workers. The total factor productivity (A) and the relative productivity of high-skilled workers (β) are allowed to depend on the number of STEM workers, thereby capturing an important feature that STEM workers are the vital input in the development of new technologies that increase total factor productivity as well as the productivity of skilled workers. The elasticity of substitution between skilled and unskilled labor is represented by $\sigma_H = 1/(1 - \rho)$. Following Ottaviano and Peri (2012) and Manacorda et al. (2012), I assume that (1) is a long-run production function in which capital is in perfectly elastic

[3] Unskilled workers are defined as those with at most high school diploma employed in non-STEM occupations.

supply and therefore can be solved out of the production function. The skilled labor input (H_t) is a combination of labor input of STEM and non-STEM college-educated workers:

$$H_t = [\gamma_t S_t^{\mu} + (1 - \gamma_t) C_t^{\mu}]^{\frac{1}{\mu}} \tag{2}$$

where S and C represent STEM and non-STEM college labor input, respectively. $\gamma_t \in [0, 1]$ represents the share of labor employed as STEM workers, while $\sigma_{sc} = 1/(1-\mu)$ represents the elasticity of substitution between the STEM and non-STEM college workers. It is plausible for STEM and non-STEM college-educated workers to be perfect substitutes in this framework. However, STEM workers are different than non-STEM college-educated workers in their unique capability of generating innovations and ideas that increase workers' productivity.

So far, the framework is analogous to Peri et al. (2015). Extending their model, I considered that the STEM labor input is an aggregate of labor input of STEM workers with different level of educational attainments:

$$S_t = [\sum_e \theta_{set} S_{et}^{\pi}]^{\frac{1}{\pi}} \tag{3}$$

where e denotes education group and $\sigma_{se} = 1/(1 - \pi)$ is the elasticity of substitution of STEM workers between different education levels. θ_{set} reflects the relative efficiency of STEM workers with education e, with $\sum_e \theta_{set} = 1$. Similarly as before, the supply of labor in each education group within STEM sector is an aggregate of contribution of STEM workers with different age:

$$S_{et} = [\sum_{a} \theta_{seat} S_{eat}^{\lambda}]^{\frac{1}{\lambda}} \tag{4}$$

where a denotes age group and $\sigma_{sa} = 1/(1-\lambda)$ is the elasticity of substitution of STEM workers between different age groups. θ_{seat} reflects relative efficiency of STEM workers with age a within education group e, with $\sum_a \theta_{seat} = 1$. I do not assume the relative efficiency term θ_{seat} to be constant over time (i.e., there is no age-biased technological progress) because this assumption might be to restrictive, which I will discuss in greater detail later. Finally, the labor supply of workers in each education-age (skill) group within STEM fields is a combination of labor input of native-born and immigrant workers:

$$S_{eat} = [\theta_{seat}^{N} N_{seat}^{\eta} + \theta_{seat}^{I} I_{seat}^{\eta}]^{\frac{1}{\eta}} \tag{5}$$

where N and I denote U.S. and foreign-born STEM workers, respectively. $\sigma_{sn} = 1/(1-\eta)$ is one of the main parameters of interest as it describes the degree of substitutability between similarly skilled U.S.- and foreign-born STEM workers. Similarly as before, θ_{seat}^{N} and θ_{seat}^{I} are the relative efficiency of U.S. and foreign-born STEM workers with education e and age a. Without loss of generality, I assume $\theta_{seat}^{N} + \theta_{seat}^{I} = 1$. Equation (5) allows the relative efficiency of foreign-born STEM workers to be different along education, age, and time. This can be caused by discrimination, selective migration, or changes in the quality of immigrant stock across cohorts.

In a competitive labor market, the wages for STEM workers with education e and age a are equal to their marginal product (for notational simplicity, I omit the dependence of

A and β on the number of STEM workers S):

$$\ln W^{i}_{seat} = \frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln\beta_t + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})\ln H_t + \ln\gamma_t + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}})\ln S_t + \ln\theta_{set} + \\ + (\frac{1}{\sigma_{sa}} - \frac{1}{\sigma_{se}})\ln S_{et} + \ln\theta_{seat} + (\frac{1}{\sigma_{sn}} - \frac{1}{\sigma_{sa}})\ln S_{eat} + \ln\theta^{i}_{seat} - \frac{1}{\sigma_{sn}}\ln i_{seat} \tag{6}$$

where $i = N, I$ denotes STEM workers' nativity (U.S. or foreign born). Similarly, the wages for non-STEM college and low skilled workers are given by:

$$\ln W^{c}_{t} = \frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln\beta_t + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})\ln H_t + \ln\gamma_t - \frac{1}{\sigma_{sc}}\ln C_t \tag{7}$$

$$\ln W^{L}_{t} = \frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln(1-\beta_t) - \frac{1}{\sigma_H}\ln L_t \tag{8}$$

Ignoring the time subscript, if I denote changes in the numbers of foreign STEM workers in each education-age cell as $d\ln I_{sea}$, then the impact of foreign STEM labor supply inflow on U.S.-born STEM worker with education e and age a is given by:[4]

$$d\ln W^{N}_{sea} = \frac{1}{\sigma_H}d\ln Y + \psi_A d\ln S + \psi_B d\ln S + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})d\ln H + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}})d\ln S + \\ + (\frac{1}{\sigma_{sa}} - \frac{1}{\sigma_{se}})d\ln S_e + (\frac{1}{\sigma_{sn}} - \frac{1}{\sigma_{sa}})d\ln S_{ea} \tag{9}$$

where $\psi_A = \frac{\partial\ln A}{\partial\ln S}$ and $\psi_B = \frac{\partial\ln\beta}{\partial\ln S}$ are the spillover (externalities) effects – that is, the change in TFP and skill-biased technological progress caused by new innovations and ideas that are generated by STEM workers. Similarly, the impact on immigrant STEM worker with

[4]The expressions to calculate each component from equation (9) and (10) are given in the Appendix.

education e and age a is

$$d \ln W^I_{sea} = \frac{1}{\sigma_H} d \ln Y + \psi_A d \ln S + \psi_B d \ln S + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H}) d \ln H + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}}) d \ln S + \\ + (\frac{1}{\sigma_{sa}} - \frac{1}{\sigma_{se}}) d \ln S_e + (\frac{1}{\sigma_{sn}} - \frac{1}{\sigma_{sa}}) d \ln S_{ea} - \frac{1}{\sigma_{sn}} d \ln I_{sea} \quad (10)$$

Equation (9) shows that the direct partial wage effect (i.e., when Y, H, S, and S_e are held constant; this is obtainable by following the aggregate skill cell regression approach based on the work of Borjas (2003) by controlling for year-specific effects along with characteristics-by-year specific effects in a regression framework) of STEM immigration on native STEM workers will depend on the size of σ_{sa} and σ_{sn} parameters.[5] If the complementarity between U.S.-born workers and immigrants within closely defined skill groups in STEM fields is high enough to dominate the degree of complementarity between workers of different age ($\frac{1}{\sigma_{sn}} > \frac{1}{\sigma_{sa}}$), then the direct partial wage effect will be positive–that is, an influx of STEM immigrants workers into a skill group would increase the wage of U.S.-born STEM workers in that skill group.

As noted by Ottaviano and Peri (2012), however, the direct partial wage effect obtained through regression may be uninformative because it does not take into account the pattern of immigration across groups and omits all the cross-group effects. If there is some complementarity between older and younger workers with similar education within the STEM sector, and immigration increases the relative supply of young STEM workers, then the wages of older STEM workers are expected to increase through some complementarity of older and young workers in the STEM sector. Furthermore, estimating direct partial wage effect in this case implies that the productivity spillover effects of

[5]Since the seminal work by Borjas (2003), there are many studies (e.g. Bonin, 2005; Steinhardt, 2011; Bratsberg and Raaum, 2012; Bratsberg et al., 2014) estimating the direct partial wage effect obtained using aggregate skill cell regression approach.

STEM workers are ignored (i.e., when S is held constant, it follows that the externalities effects – ψ_A and ψ_B – are omitted).[6] Therefore, to fully capture the total impact of STEM immigration, I use equations (9) and (10) to estimate the total wage effect of STEM immigration that takes into account the pattern of immigration across all groups within STEM fields, the degree of substitution within and across groups, and the potential spillover effects of STEM workers.

For non-STEM college and low skilled workers, the effect of STEM immigration is:

$$d\ln W^c = \frac{1}{\sigma_H} d\ln Y + \psi_A d\ln S + \psi_B d\ln S + \left(\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H}\right) d\ln H \tag{11}$$

$$d\ln W^L = \frac{1}{\sigma_H} d\ln Y + \psi_A d\ln S - \frac{\beta}{1-\beta}\psi_B d\ln S \tag{12}$$

As shown in Equation (12), it follows that although unskilled workers gain from an influx of foreign-born STEM workers through an increase in TFP and some complementarity with highly skilled workers, STEM immigration may potentially reduce the wages of unskilled workers by inducing technological progress that favors skilled workers.

3 Data

The data used in the analysis were from IPUMS 5% 2000 Census and American Community Survey (ACS) 2001 to 2015 (Ruggles et al., 2015). Following the literature (e.g., Katz and Murphy, 1992; Borjas et al., 2008; Ottaviano and Peri, 2012), I constructed two slightly different samples to produce measures of labor supply and average wage by cell. The wage sample was designed to obtain an accurate price of labor and consisted

[6] Alternatively, one can see from equation (6) that year fixed effect would capture the effect of foreign STEM inflow on TFP and skill-biased technological progress.

of full-time workers who are not self-employed or currently in school.[7] As a measure of wages, I used real weekly earnings obtained by dividing the annual salary and income, INCWAGE, with weeks worked in a year (WKSWORK) and then deflating it using the CPI.[8] Then, to obtain the average weekly wages in a cell, I took the weighted average of real weekly earnings where the weights are the hours worked by an individual times his or her person weight (PERWT).[9]

To construct the labor supply sample, I included all workers (including self-employed, in-school, or part-time workers) because the supply in each cell should reflect the total labor supply provided by all foreign and U.S.-born workers (Borjas et al., 2008). Although I also provide the result when labor hours are used, my preferred measure of labor supply is the number of employed workers. The reason for this is that because the measure of labor hours are usually obtained by multiplying usual hours worked per week with weeks worked in a year, measurement error in either usual hours or weeks worked may cause a non-classical measurement error bias resulting from the error in the weighted average of real weekly earnings systematically correlated with the measure of labor hours.[10]

In regression analysis to obtain elasticity parameter estimates that were necessary to estimate the wage effect of STEM immigration, I mainly considered the sample of men of age 28 to 62 who are not living in a group quarter and worked at least one week in the previous year.[11] This is because women's labor supply is more likely to

[7]Full-time workers were defined as those working at least 40 weeks in a year and at least 35 hours in the usual workweek. IPUMS variable SCHOOL was used to determine if an individual is attending school.

[8]Because weeks worked in a year are only available on a bracketed basis after 2007, I follow Ottaviano and Peri (2012) and Borjas et al. (2012) by imputing weeks worked using the mid-value of the range in a bracket. For example, on a 1-13 weeks bracket, I imputed 6.5 weeks. On a 14-26 weeks bracket, I imputed 20 weeks, and so on.

[9]The hours worked is obtained by multiplying usual hours worked per week (UHRSWORK) with weeks worked.

[10]This problem is similar to the "division bias" case outlined in Borjas (1980).

[11]The age range is chosen to allow the individual to complete his or her education, including post-graduate degree, and to abstract away from retirement age.

be endogenous to wages relative to men, and the inclusion of women in the sample may have a compositional effect that affects the within-group trends in the wages of workers in a way that is hard to assess (Borjas et al., 2008). In simulating the wage effect of STEM immigration, however, I include both men and women in the analysis. Because highly skilled STEM immigration is mainly focused on workers with college degrees, my preferred specification divides STEM workers into three education groups: less than bachelor's degree, bachelor's degree, and post-graduates.[12] Similar to Card and Lemieux (2001), I classified STEM workers in each education level into seven five-year-age groups (28-32, 33-37, 38-42, 43-47, 48-52, 53-57, 58-62). Following Borjas et al. (2012), all regressions in the analysis used mean log wages and appropriate regression weight (i.e., the inverse of the sampling variance of the dependent variable).

There are a few definitions of STEM occupations (e.g., Langdon et al., 2011; Peri et al., 2015). However, I used the broad STEM occupation classification outlined by National Science Foundation as a guideline to determine the STEM classification to be used in the analysis (National Science Board, 2016).[13] As such, my preferred STEM classification is the Census Bureau 2010 STEM occupations code list, which closely follows the NSF definition. As the Census' Standard Occupational Classification (SOC) expanded over time as a result of technological progress (Lin, 2011), I crosswalk the STEM occupation code list 2010 from the Census Bureau to the time consistent IPUMS 2010 occupational classification codes. I also used Peri et al. (2015) top 4% skill-based STEM classification as a robustness check in the regression analyses to obtain elasticity parameters. It should

[12]Indeed, USCIS requires that highly skilled visa (H-1B) applicants to have at least bachelor's degrees or specialized training/experience that is equivalent to the completion of a U.S. bachelor's degree (USCIS, 2017). An exemption can be made if the applicant holds an unrestricted state license or certification that authorizes the applicant to fully practice the specialty occupation. In the fiscal years 2012 through 2015, approximately only 1% of new H-1B petition was approved for workers without a bachelor's or advanced degree in each year.

[13]NSF classifies "biological, agricultural, and environmental life scientists," "computer and mathematical scientists," "physical scientists," "social scientists," "engineers," "S&E managers," and "S&E technicians and technologists" as STEM occupations. It excludes "health-related" occupations.

be noted that the Census STEM definition is preferable because Peri et al. (2015) STEM classification is based on IPUMS 1990 occupational classification codes and therefore may exclude new occupation titles that became common after the beginning of the digital era.[14] Unless otherwise specified, the analysis used Census 2010 STEM occupations classification. The list of STEM occupations is provided in Table 1 in the Appendix.

4 Estimation

To estimate the wage effect of STEM immigration as implied by equations (9), (10), (11) and (12), I need to find estimates of all the own and cross-group elasticity of substitution parameters along with estimates of the externalities elasticity associated with highly skilled STEM workers. I use estimates obtained by Peri et al. (2015) for externalities elasticity, which are approximately 0.22 and 0.10 for ψ_A and ψ_B, respectively. The estimate of ψ_A is close to the Bound et al. (2017) estimate of the increase in TFP in the IT sector that is contributed to the number of computer scientists in the sector (0.233). As implied by nested CES framework above, I need an estimate of S_{eat} to estimate σ_{sa}. Moreover, to estimate CES-weighted labor aggregate S_{eat}, I need estimates of θ^N_{seat} and θ^I_{seat} along with η as implied by equation (5). Similarly, to estimate σ_{se}, σ_{sc}, and σ_H, I need estimates of S_{et} and S_t along with H_t. It should be noted, however, that it is possible to bypass the calculation of the CES-weighted labor aggregate S_{eat}, S_{et}, S_t, and H_t by using the actual number of workers in each group because they are highly correlated with each other and the distinction does not substantially affect the results (Borjas, 2003; Ottaviano and Peri, 2012). In the steps below, I proceed iteratively and present the results obtained using the

[14] For example, the "computer and information systems managers" that are part of STEM in IPUMS 2010 occupation codes are classified as "managers and administrators, n.e.c." in IPUMS 1990 codes, which is not part of STEM occupations in Peri et al. (2015). Peri et al. (2015) also provide other possible ways to classify STEM occupation. However, they often include non-S&E and health-related occupations that are not part of STEM occupations according to NSF.

actual number of workers and CES-weighted labor aggregate.

4.1 Estimating σ_{sn}, θ^N_{seat}, and θ^I_{seat}

To estimate σ_{sn}, θ^N_{seat}, and θ^I_{seat}, I can derive the wage differential between U.S.-born workers and immigrants in each skill group within STEM sector using equation (6):

$$\ln \frac{W^I_{seat}}{W^N_{seat}} = \ln \frac{\theta^I_{seat}}{\theta^N_{seat}} - \frac{1}{\sigma_{sn}} \ln \frac{I_{seat}}{N_{seat}} \tag{13}$$

Equation (13) implies that the relative wages of U.S.-born workers and immigrants in each skill group within the STEM sector are inversely related to their relative supply. If immigrants and native workers are perfect substitutes ($\frac{1}{\sigma_{sn}} = 0$), then changes in the relative employment of natives and immigrants will have no effect on their relative wages.

Similar to Borjas et al. (2012), I assume the relative efficiency term $\ln \frac{\theta^I_{seat}}{\theta^N_{seat}}$ can be captured by year, education, and age fixed effects along with their interactions:

$$\ln \frac{\theta^I_{seat}}{\theta^N_{seat}} = \delta_t + \delta_{ea} + \delta_{et} + \delta_{at} \tag{14}$$

It follows that I can obtain an estimate of σ_{sn} by estimating the following:

$$\ln \frac{W^I_{seat}}{W^N_{seat}} = \delta_t + \delta_{ea} + \delta_{et} + \delta_{at} - \frac{1}{\sigma_{sn}} \ln \frac{I_{seat}}{N_{seat}} \tag{15}$$

where the estimates on the year, education, and age fixed effects along with their interactions provide estimates of θ^N_{seat} and θ^I_{seat}. I use these estimates along with an estimate of η to calculate S_{eat}.

4.2 Estimating σ_{sa} and θ_{seat}

Given the estimate of S_{eat}, I can then obtain the estimates of σ_{sa} and θ_{seat}. In a competitive labor market, the wages of STEM workers with education e and age a are given by

$$\ln W_{seat} = \underbrace{\frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln \beta_t + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})\ln H_t + \ln \gamma_t + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}})\ln S_t}_{\delta_t}$$
$$+ \underbrace{\ln \theta_{set} + (\frac{1}{\sigma_{sa}} - \frac{1}{\sigma_{se}})\ln S_{et}}_{\delta_{et}} + \ln \theta_{seat} - \frac{1}{\sigma_{sa}}\ln S_{eat} \quad (16)$$

Note that the first and second term of the right-hand side can be captured by year fixed effects along with its interaction with education fixed effects. I assume that the relative efficiency term $\ln \theta_{seat}$ can be captured by the interaction of education-age and year-age fixed effects:

$$\ln \theta_{seat} = \delta_{ea} + \delta_{at} \quad (17)$$

It should be noted that studies that try to estimate the wage effect of overall immigration usually does not include year-age fixed effects (δ_{at}) by assuming that there is no age-biased technological change (e.g., Borjas, 2003; Ottaviano and Peri, 2012; Manacorda et al., 2012). However, a closer look at the data suggests that this assumption might be too restrictive, especially for highly educated STEM workers. Figures (2) and (3) show the evolution of wages between older and young STEM workers since 2000.[15] We can see that the trend in wages between the old and the young started to diverge around 2008 for bachelor's and post-graduate degree holders. Because older and young workers might be imperfect

[15] "Old" is defined as workers of 53 to 62 years old, while "young" consists of workers of 28 to 37 years old.

substitute (e.g., Card and Lemieux, 2001), one may argue that this result may be driven by the decline of relative supply of older workers with a bachelor's or post-graduate degree in STEM fields. This argument is partly true because the relative supply of older workers with a post-graduate degree did decline around the same time as the divergence of the trend in wages between the old and the young (Figure 4). However, the relative supply of older workers with a bachelor's degree in STEM fields did not decline, which implies that the relative productivity of older workers needs to increase to explain the divergence in the trend of wages between old and young STEM workers with bachelor's degree. These results imply that I need to take into account the changes over time in relative efficiency across age groups within an educational level in STEM fields, at least for the sample period considered in this study.[16] Therefore, to obtain an estimate of σ_{sa}, I estimate the following:

$$\ln W_{seat} = \delta_t + \delta_{et} + \delta_{ea} + \delta_{at} - \frac{1}{\sigma_{sa}} \ln S_{eat} \tag{18}$$

where the coefficients on δ_{ea} and δ_{at} provide an estimate of θ_{seat} which can then be used to estimate S_{et}. As noted by Borjas (2003), however, the OLS regression of equation (18) may lead to a biased estimate of σ_{sa} because the supply of workers across different education groups is likely to be endogenous over the period of consideration in this study. Therefore, following previous literature (e.g., Borjas, 2003; Ottaviano and Peri, 2012), I use the number of immigrants in a skill group as an instrument for total labor supply in that particular group. This instrument would be valid under the assumption that the changes in immigrants' labor supply in each skill group is driven by supply shocks such

[16]This result mirrors the findings of Burtless (2013), who found older workers are more productive compared to younger workers in recent years from CPS data. One may want to include education-age-year fixed effects to fully capture the term $\ln \theta_{seat}$. However, this is not possible because there would be as many fixed effects as there are observations.

as migration costs after controlling for fixed effects. This assumption, however, may not hold because income-maximizing behavior by potential immigrants may generate larger inflows into skill cells that have relatively higher wages (Borjas, 2003). Therefore, it should be noted that the use of immigrants' labor supply as the instrument may still overstate the estimate of σ_{sa}.

4.3 Estimating σ_{se} and θ_{set}

Given the estimate of S_{et}, I can then obtain the estimates of σ_{se} and θ_{set}. In a competitive labor market, the wages of workers with education e in STEM sector are given by

$$\ln W_{set} = \underbrace{\frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln \beta_t + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})\ln H_t + \ln \gamma_t + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}})\ln S_t +}_{\delta_t}$$
$$+ \ln \theta_{set} - \frac{1}{\sigma_{se}}\ln S_{et} \tag{19}$$

Similarly as before, the first term of the right-hand side can be captured by year fixed effects. Note that I cannot use year-education fixed effects to capture the relative efficiency term $\ln \theta_{set}$ because I would not have an adequate degree of freedom to identify σ_{se}. Following Borjas (2003), I assume that $\ln \theta_{set}$ can be approximated by education fixed effects along with its interaction with linear time trend. Therefore, to obtain an estimate of σ_{se}, I estimate the following:

$$\ln W_{set} = \delta_t + \delta_e + \mathit{lineartrend} \times \delta_e - \frac{1}{\sigma_{se}}\ln S_{et} \tag{20}$$

where the estimates on δ_e and its interaction with linear time trend provide an estimate of θ_{set}. Similarly as before, I use immigrants' labor supply as an instrument in the estimation. After obtaining all the estimates, I can then compute an estimate of S_t.

4.4 Estimating σ_{sc} and γ_t

To obtain an estimate of σ_{sc}, I can use wage differential between STEM and non-STEM college workers:

$$\ln \frac{W_{st}}{W_{ct}} = \ln \frac{\gamma_t}{(1-\gamma_t)} - \frac{1}{\sigma_{sc}} \ln \frac{S_t}{C_t} \tag{21}$$

where I assume that the relative efficiency term $\ln \frac{\gamma_t}{(1-\gamma_t)}$ can be captured by linear time trend. It follows that I can obtain an estimate of σ_{sc} by estimating the following:

$$\ln \frac{W_{st}}{W_{ct}} = \textit{lineartrend} - \frac{1}{\sigma_{sc}} \ln \frac{S_t}{C_t} \tag{22}$$

where the linear trend provides an estimate of γ_t. I can then calculate an estimate of H_t using estimates of γ_t and S_t along with the actual number of non-STEM college workers at time t (C_t).

4.5 Estimating σ_H

Finally, I can obtain the last elasticity of substitution parameter (σ_H) by using the wage differential between skilled and unskilled workers:

$$\ln \frac{W_t^H}{W_t^L} = \ln \frac{\beta_t}{(1-\beta_t)} - \frac{1}{\sigma_H} \ln \frac{H_t}{L_t} \tag{23}$$

where following Katz and Murphy (1992), I assume the term $\ln \frac{\beta_t}{(1-\beta_t)}$ can be approximated by linear time trend.

5 Estimates of Elasticity of Substitution

5.1 Estimate of σ_{sn}

Table 2 provides an estimate of the elasticity of substitution between similarly skilled U.S. and foreign-born STEM workers. The "Census" column use Census 2010 STEM classification while "Skill-Based" use Peri et al. (2015) top 4% skill-based STEM classification for the analysis. The baseline estimates show that similarly skilled U.S. and foreign-born workers within the STEM sector are imperfect substitutes with an elasticity of substitution of approximately 13. Rows 2 to 5 of Table 2 use the alternative specifications to estimate $\frac{1}{\sigma_{sn}}$. In row 2, I use labor hours instead of employment as a measure of labor supply. In row 3, I include women in the sample. In row 4, I split the "less than bachelor's degree" group into "some college" and "at most high school graduates." In row 5, I further split the "at most high school graduates" group into "high school dropout" and "high school graduates." The results of imperfect substitution between similarly skilled U.S. and foreign-born STEM workers hold under these alternative specifications, with a value of $\frac{1}{\sigma_{sn}}$ ranging from -0.056 to -0.086. I took the most conservative value (σ_{sn} = 18) to estimate the wage effect of STEM immigration. This finding implies that the impact of STEM immigration would be concentrated among immigrant STEM workers themselves, while its effect on U.S.-born STEM workers would be mitigated.

There are a few reasons why similarly skilled U.S. and foreign-born STEM workers can be an imperfect substitute. For example, Chiswick (1978) found that the return to education and experience obtained abroad is lower compared to those obtained in the U.S., implying that U.S. employers may treat foreign education and experience as not equal to those acquired in the United States.[17] Peri and Sparber (2009) argued that immigrants

[17]Dustmann et al. (2013) argue that because immigrants may experience "downgrading" of skills upon

might specialize in occupations that require less interactive and communication skills to maximize their wages. In a follow-up study, Peri and Sparber (2011) found that immigrants with graduate degrees specialize in occupations that require more quantitative and analytical skills, while their U.S.-born counterparts specialize in occupations requiring communication and interactive skills. To test whether specialization also occurs within the STEM sector, I calculate Duncan Dissimilarity Index to estimate occupation segregation between the U.S.- and foreign-born workers in STEM sector (Table 7). The index does suggest that there is specialization, especially for workers with a post-graduate degree, by which approximately 24 to 29 percent of U.S. or foreign-born STEM workers would have to move to other STEM jobs to equalize occupational distribution in this education group.

5.2 Other Elasticity Parameter Estimates

Table 3 provides estimates of the elasticity of substitution between workers of different ages with similar educational levels in the STEM sector. The estimates range from 0.001 to -0.076, depending on the specification used. However, as noted above, the use of hours as labor supply measure may lead to non-classical measurement error bias caused by the error in the weighted average of real weekly earnings systematically correlated with the measure of labor hours. Similarly, the use of a pooled (men and women) sample might not be preferable because women's labor supply is more likely to be endogenous

arrival, pre-allocating immigrants based on their observable characteristics may not be appropriate because immigrants might be competing with U.S.-born workers at the other parts of skill distribution, which is different from the one assigned to them based on observable characteristics. They propose, therefore, to investigate the impact of immigration on a specific portion of native wage distribution because the estimate would not be affected by downgrading. However, as noted by Ottaviano and Peri (2012), their approach assumes the same wage effect of immigration in any other group on natives – that is, they consider only the wage effect of overall inflow of immigrants, even though the wage effect may also depend on the distribution of immigrants across skill groups as implied by nested CES framework. Furthermore, to obtain enough observations for their estimates, Dustmann et al. (2013) consider UK provinces as different labor markets, and therefore, they may not address the problems outlined by Borjas (2003, 2014).

to wages, and the inclusion of women in the sample may have a compositional effect that affects the within-group trends in the wages of workers in a way that is difficult to assess (Borjas et al., 2008). Therefore, estimates obtained from rows 1 and 2 are preferable to estimates from rows 3 and 4.

As noted by Borjas et al. (2012), it may be necessary to use four or five education groups to examine the wage effect of *overall* immigration because immigration in the United States has mainly increased the size of some specific groups such as high school dropouts and workers with post-graduate degrees. However, this paper is examining the impact of highly skilled STEM immigration, whereas the focus of recent policy debates, such as H1-B visas, is on increasing the number of immigrant workers with at least a bachelor's degree. Furthermore, the use of a larger number of education groups in a CES framework comes at a cost. For example, in a five education groups framework, the elasticity of substitution between high school dropouts and high school graduates is restricted to be the same as between high school dropouts and college graduates, even though it is quite likely that the degree of substitutability in the first case is higher than the second one. Therefore, the baseline model with three education groups (less than bachelor's degree, bachelor's degree, and post-graduate degree) should be able to capture the impact of STEM immigration, while minimizing the cost associated with cross-elasticities restriction. One way to test whether it is appropriate to combine "high school dropouts," "high school graduates," and "some college" into one group is by estimating the degree of substitutability of workers within the "less than bachelor's degree" group. The estimates from Table 8 show that I cannot reject that these workers are perfect substitutes in any of the specifications used. I interpret the robustness of this result as suggesting that within the highly specialized/skilled STEM sector, "high school dropouts," "high school graduates," and "some college" groups can be reasonably combined into a single "less than bachelor's degree" group, and therefore, the estimates of $\frac{1}{\sigma_{sa}}$ obtained from rows 1 and 2 are preferable to those in rows 4 and 5. I use the value of 13 for σ_{sa}, which approximates the estimates obtained from the first two rows–to estimate the wage effect of STEM immigration. My estimate of the elasticity of substitution between age groups within an education group in STEM sector (~13) is relatively higher compared to Card and Lemieux (2001), who did not differentiate between the STEM and non-STEM workers (~5). However, this estimate mirrors the finding of Kerr et al. (2015), who found that older workers in STEM occupations are more vulnerable to displacement by young skilled immigrants and estimated the elasticity of substitution across age groups of 14.6 for engineers, 7.4 for scientists, and 27.4 for computer-related occupations.

Table 4 provides estimates of the elasticity of substitution between workers of different educational attainments in the STEM sector. Similarly as before, I use the value of 6 for σ_{se}, which approximates the estimates from the baseline model with three education groups, to estimate the total wage effect of STEM immigration. This elasticity of substitution between education groups in the STEM sector is larger compared to the estimates obtained without differentiating between the STEM and non-STEM workers. For example, Borjas (2003) estimated that the inverse elasticity of substitution between workers across education groups to be -0.759 (with standard error equal to 0.582), using the elasticity of substitution value equal to 1.3 in estimating the wage effect of overall immigration. Similarly, Borjas and Katz (2007) estimated that the inverse elasticity of substitution between workers across education groups to be -0.412 (with standard error equal to 0.312), using the elasticity of substitution value equal to 2.4 in estimating the wage effect of Mexican immigration. Comparing my estimate of the elasticity of substitution between workers across education groups in STEM sector with the estimates of Borjas (2003) and Borjas and Katz (2007) who did not differentiate between STEM and non-STEM workers, the result suggests that the degree of substitution between workers across education groups in the STEM sector is higher than between workers across education groups in the non-STEM sector.

Table 5 provides estimates for σ_{sc}. Similar to Peri et al. (2015), I cannot reject that STEM and non-STEM college workers are perfect substitutes in any of the specifications used. Therefore, I used $\sigma_{sc} = \infty$ to estimate the wage effect of STEM immigration. Finally, Table 6 provides estimates for σ_H. The literature provides some guidance on the value of σ_H. In their influential study, Katz and Murphy (1992) found the estimate of σ_H to be 1.4. Ottaviano and Peri (2012) provided estimates ranging from 1.5 to 3.1. I used the value of 2, which is the value that is also widely used in the literature.

6 Wage Effect

6.1 Foreign STEM Supply Shock 2000-2015

Now, I can use the elasticity parameter estimates obtained in the previous section to calculate the long-run wage effect of 2000-2015 foreign STEM supply shock on the preexisting workforce. In estimating the long-run effect, I used the actual changes in the supply of immigrants from 2000 to 2015 in each cell within STEM sector, holding the employment level of non-STEM and U.S.-born STEM workers constant at their 2000 level. Therefore, it should be noted that the wage effect estimate that is presented in this analysis is the wage effect on the preexisting workforce in 2000 in the case that they experience foreign STEM supply shock in the magnitude that is as large as the changes in supply caused by immigrants from 2000 to 2015 (as observed in Table 1). To see how much of the wage effect and economic benefit of STEM immigration can be attributed to the generation of ideas associated with high-skilled STEM workers, I also report the result of the estimation assuming that STEM immigration does not have an effect on the total factor productivity and skill-biased technological progress in 'without externalities' column (i.e., ψ_A and ψ_B are set to be equal to zero). Considering that the magnitude of positive externalities of high-skilled STEM immigration is still widely debated in the literature (Borjas and Doran, 2012; Moser et al., 2014; Doran et al., 2016), the wage effect of foreign STEM labor supply shock in the absence of spillover effects can provide an approximation of the lower bound of the effect of STEM immigration.

Figure 4 and 5 show the results of the wage effects across education-age groups in STEM sector.[18] The wage gains of U.S.-born STEM workers with less than a bachelor's degree is around 5 to 6 percent, and the gains are relatively similar for both young and older workers. The pattern of the wage gains being relatively similar between young and older workers is also found for workers with a bachelor's and post-graduate degree. This finding reflects relatively high substitutability between young and older workers in the STEM sector. Panel A of Table 9 shows the wage effect estimates across the educational level. As expected, workers with post-graduate degree benefited the least (3.14%) because the influx of foreign-born STEM workers during this period is more concentrated in this group. Comparing these estimates with the ones without the spillover effects, the results suggest that the positive effect of STEM immigration comes mainly through the generation of ideas that increase the overall productivity of U.S.-born STEM workers. In the absence of spillover effects, the impact of 2000-2015 foreign STEM supply shift on the average wage of U.S.-born STEM workers is approximately 0.58%, while this number increased by about 4.09 percentage points when the positive

[18] "Perfect Substitute" shows the result when similarly skilled U.S. and foreign-born STEM workers are assumed to be perfectly substitutable in production. In this case, the wage effects across skill groups depicted in Figure 4 and 5 are the same for both U.S. and foreign-born STEM workers.

externalities associated with an inflow of high-skilled STEM workers are taken into account.

In the case of earlier immigrant STEM workers, the wage effect of 2000-2015 foreign STEM supply shocks varies widely across age groups (Figure 5). Older workers were more adversely affected relative to the young, reflecting the increase in the supply that is relatively larger among older workers and the imperfect substitutability between similarly skilled U.S. and foreign STEM workers so that the impact of STEM immigration resulted in more competition among immigrants in that particular skill group. On average, the wage of earlier STEM immigrants declines by -0.07% (Panel A of Table 9). The average, however, masks a higher adverse impact among foreign-born STEM workers with a post-graduate degree (-1.56%). If the productivity spillovers associated with high-skilled STEM immigration are not taken into account, the loss of earlier STEM immigrants is even larger. On average, the wage of foreign-born STEM workers declines by 4.16% if the positive externalities associated with an inflow of high-skilled STEM workers are not taken into account.

Although the data rejects the model in which similarly skilled U.S. and foreign-born STEM workers are perfect substitutes, it might be interesting to see how much the results change if they are assumed to be perfectly substitutable in production. In this case, the effect of 2000-2015 foreign STEM labor supply shock increases the average wage of all STEM workers (foreign and U.S-born) by approximately 3.85% (Table 10). Similar to before, the positive effect mainly comes from the positive externalities associated with an influx of high-skilled STEM workers. In the absence of these externalities, the average wage of all STEM workers declines by a relatively small amount (0.24%).

For low skilled workers, the wage effect is approximately 1.41% (Panel A Table 11). This wage gain reflects the positive effect of high-skilled STEM immigration through the increase in TFP that outweighs its adverse effect which comes from inducing technological progress that favors skilled workers. For college non-STEM workers, the wage gain is bigger at 3.85%.

Given the wage effect estimates across skill groups, I can now make a simple back of the envelope cost-benefit calculation of the economic benefit of foreign STEM labor supply shocks from 2000 to 2015 for U.S.-born workers. To estimate the benefit/loss from STEM immigration, I used the annual earnings of workers between age 28 to 62 who worked at least a week and reported positive income. The benefit/loss in each skill group is calculated by multiplying the average earnings in a group with its estimated wage effect and the number of workers in the group. Then, the benefit/loss in each skill group can be summed up to get the overall benefit/loss. The result of this simple cost-benefit calculation is reported in Table 12.

In the long run, the 2000-2015 foreign STEM labor supply shock increases U.S.-born workers' income by approximately 103 billion USD or 1.03% of U.S. GDP in 1999. Almost all of this benefit accrues to the productivity spillovers associated with an influx of highly-skilled STEM workers. In the absence of this productivity spillover, the impact of STEM immigration in the long-run on the U.S. economy can be expected to be relatively small.

To summarize, I estimated that although 2000-2015 foreign STEM supply shock increases U.S.-born STEM workers' average wage by 4.67%, native STEM workers with higher educational attainment experience lower wage gain. The economic benefit for U.S.-born workers is estimated to be approximately 1.03% of U.S. GDP in 1999, and almost all of this benefit can be attributed to the productivity spillovers associated with the influx of highly-skilled STEM workers.

6.2 H-1B Visa Reform Act of 2004

Using the framework above, I can obtain an estimate of the wage impact of the H-1B Visa Reform Act of 2004, which limits the new issuances of H-1B visas to 65,000 per year plus 20,000 for workers who have earned master's degrees or doctorates from U.S. institutions since 2004. The H-1B visa is a temporary permit that allows foreign-born workers in highly skilled specialty occupations to work in the U.S. Since 1990, the visas had been limited to 65,000 new issuances annually, although the cap had been raised to 115,000 in 1999 and 2000 and then to 195,000 from 2001 to 2003 in response to high demand for the visas. Currently, the limit of new issuances has not changed since the H-1B Visa Reform Act was passed in 2004. Although the visas are not limited to workers who are employed in STEM occupations, approximately 60% of H-1B petitions for initial employment approved were for science and engineering occupations (USCIS, 2004).

Between 2004 and 2015, USCIS' press release noted some years in which the applications for H-1B visas exceed the 85,000 cap limit: 150,000 applications in the fiscal year 2008, 163,000 applications in the fiscal year 2009, 124,000 in the fiscal year 2014, and 172,500 applications in the fiscal year 2015. Since about 40% of the visas were issued for workers in non-STEM occupations, there would be approximately 161,700 additional STEM workers entering the U.S. by 2015 in the absence of the reform. In the fiscal year 2004, approximately 80% of new H-1B visas were issued to workers under 35 years old (USCIS, 2004). Most of them were college-educated (approximately 48% and 51% were bachelor's degree and post-graduate degree holders, respectively).[19] Considering the historical distribution of age and educational level of workers whose initial employment petition was approved, it is likely that the large share of additional STEM workers en-

[19]Similar to 2004 fiscal year, the pattern that individuals whose initial petition was approved were relatively young college-educated workers holds for fiscal years 2005 through 2015.

tering the U.S. in the absence of the reform would be relatively young college-educated workers. For estimation purpose, I assume that 48% and 51% of these 161,700 additional STEM workers were bachelor's and post-graduate degree holders, respectively, whereas the other 1% are workers with less than a bachelor's degree. Within each educational group, I assume that 30% of these additional workers are between 28 and 33 years old, 30% of these additional workers are between 34 and 37 years old, 10% of these additional workers are between age 38 and 42 years old, 10% of these additional workers are between 43 and 47 years old, 10% of these additional workers are between 48 and 52 years, and the other 10% of these additional workers are divided equally into the remaining age groups. The wage effects of this counterfactual simulation for both U.S. and foreign STEM workers across age groups are shown in Figures 6 and 7.

The wage effects of 2000-2015 foreign STEM supply shock in the absence of the H-1B Visa reform for U.S. STEM workers across the education-age group are relatively similar to the case when there is reform. This is because the estimated additional number of STEM workers between 2004 and 2015 in the absence of the reform is relatively small to substantially affect the result across education-age group during this period. Panel B of Table 9 shows the estimates of how much 2000-2015 foreign STEM supply shock would affect the wage of STEM workers across education groups in the absence of the H-1B Visa Reform Act. Because the estimates in Panel B are the effects of the changes in the supply of STEM workers caused by both the absence of reform and the actual changes of STEM immigrants from 2000 and 2015, the difference in estimates between Panel A and Panel B can, therefore, be thought of as the effect of the enacted reform as of 2015.

If the reform had not been enacted, the wage gains for U.S.-born STEM workers would be 1 percentage point higher (5.67-4.67%), while the loss for earlier immigrant STEM workers would be higher by 0.02 percentage points (0.09-0.07%), a relatively small amount. The net benefit of foreign STEM labor supply shock from 2000 to 2015 in the absence of H1-B visa reform is approximately 0.22 percentage points higher (1.25-1.03%).

7 Conclusion

The foreign-born share of STEM workers in the U.S. has been increasing rapidly in recent years. As such, there are concerns that immigrants are displacing U.S. workers and exacting downward pressure on wages within the STEM sector. In this paper, I attempt to present new insights to several key issues regarding high-skilled STEM immigration in the United States.

There are a few main findings in this paper. First, similarly skilled U.S. and foreign-born STEM workers have a high but finite elasticity of substitution of approximately 18. This finding implies that the adverse impact of STEM immigration would be concentrated among immigrant STEM workers themselves, while its effect on U.S.-born STEM workers would be mitigated. Second, the 2000-2015 foreign STEM labor supply shock increases the average wage of preexisting U.S.-born STEM workers by 4.67 percent. This result, however, masks a distributional consequence of the shock as native STEM workers with higher educational attainment experience lower wage gains. Third, the economic benefit for native workers is approximately 103 billion USD or 1.03% of U.S. GDP in 1999, in which almost all of the benefit can be attributed to the generation of ideas associated with high-skilled STEM immigration which promotes the development of new technologies that increase the productivity and wage of U.S.-born workers. Finally, the average wage of U.S.-born STEM workers would have been approximately 1 percentage point higher in the absence of the H-1B Visa Reform Act of 2004.

8 Figures and Tables

Table 1: Percentage Change in Supply Across Skill Groups Within STEM Sector due to Immigrants, 2000-2015

Education	Age Group	% Change in Supply due to Change in Number of Immigrants
Less than Bachelor's Degree	28-32	-2.57%
	33-37	-2.29%
	38-42	0.23%
	43-47	1.86%
	48-52	4.48%
	53-57	7.20%
	58-62	7.43%
Bachelor's Degree	28-32	6.78%
	33-37	9.43%
	38-42	12.03%
	43-47	14.79%
	48-52	14.53%
	53-57	20.45%
	58-62	25.31%
Post-graduates	28-32	23.59%
	33-37	20.60%
	38-42	24.99%
	43-47	28.66%
	48-52	25.66%
	53-57	26.28%
	58-62	26.81%

Source: IPUMS 5% 2000 Census and ACS 2000-2015. The table shows the percentage changes in supply across skill groups within STEM fields caused by changes in the number of foreign STEM workers from 2000 to 2015 in each skill groups. The analysis used both men and women of age 28 to 62. STEM occupations are defined using Census 2010 STEM classification.

Table 2: Inverse of Elasticity of Substitution Between U.S and Foreign STEM Workers Within Skill Group ($1/\sigma_{sn}$)

	STEM		
	Census	Skill-Based	Observations
Baseline	-0.075	-0.072	336
	(0.035)	(0.038)	
	[0.044]	[0.075]	
Hours as Supply	-0.070	-0.066	336
	(0.033)	(0.035)	
	[0.044]	[0.074]	
Pooled (Men and Women)	-0.070	-0.068	336
	(0.027)	(0.029)	
	[0.019]	[0.031]	
Four Education Groups	-0.056	-0.080	448
	(0.029)	(0.026)	
	[0.064]	[0.005]	
Five Education Groups	-0.066	-0.086	560
	(0.027)	(0.024)	
	[0.018]	[0.001]	

Source: IPUMS 5% 2000 Census and ACS 2000-2015. Heteroskedastic- and cluster-robust standard errors at education-age groups in parentheses; *p*-value reported in brackets. 'Census' column shows the result using Census 2010 STEM classification. 'Skill-Based' shows the result using Peri et al. (2015) top 4% skill-based STEM classification. All regressions are weighted by the inverse of the sampling variance of the dependent variable.

Table 3: Estimates of $(1/\sigma_{sa})$

	STEM		
	Census	Skill-Based	Observations
Baseline	-0.075	-0.076	336
	(0.046)	(0.043)	
	[0.103]	[0.073]	
Efficiency Units	-0.075	-0.077	336
	(0.046)	(0.043)	
	[0.099]	[0.071]	
Hours as Supply	-0.058	-0.049	336
	(0.041)	(0.039)	
	[0.151]	[0.203]	
Pooled (Men and Women)	-0.041	-0.059	336
	(0.029)	(0.030)	
	[0.153]	[0.054]	
Four Education Groups	-0.037	-0.017	448
	(0.032)	(0.032)	
	[0.247]	[0.601]	
Five Education Groups	-0.027	0.001	560
	(0.032)	(0.033)	
	[0.403]	[0.978]	

Source: IPUMS 5% 2000 Census and ACS 2000-2015. Heteroskedastic- and cluster-robust standard errors at education-age groups in parentheses; p-value reported in brackets. 'Census' column shows the result using Census 2010 STEM classification. 'Skill-Based' shows the result using Peri et al. (2015) top 4% skill-based STEM classification. The method of estimation is 2SLS using the labor supply of immigrant workers as an instrument for total labor supply. All regressions are weighted by the inverse of the sampling variance of the dependent variable.

Table 4: Estimates of $(1/\sigma_{se})$

	STEM		
	Census	Skill-Based	Observations
Baseline	-0.147 (0.072) [0.040]	-0.179 (0.047) [0.000]	48
Efficiency Units	-0.147 (0.069) [0.034]	-0.166 (0.042) [0.000]	48
Hours as Supply	-0.123 (0.064) [0.055]	-0.162 (0.041) [0.000]	48
Pooled (Men and Women)	-0.080 (0.085) [0.347]	-0.128 (0.083) [0.124]	48
Four Education Groups	-0.071 (0.107) [0.504]	-0.127 (0.062) [0.040]	64
Five Education Groups	-0.055 (0.081) [0.496]	-0.092 (0.071) [0.196]	80

Source: IPUMS 5% 2000 Census and ACS 2000-2015. Heteroskedastic- and cluster-robust standard errors at education groups in parentheses; p-value reported in brackets. 'Census' column shows the result using Census 2010 STEM classification. 'Skill-Based' shows the result using Peri et al. (2015) top 4% skill-based STEM classification. The method of estimation is 2SLS using the number of immigrant workers as an instrument for total the labor supply of immigrant workers as an instrument for total labor supply. All regressions are weighted by the inverse of the sampling variance of the dependent variable.

Table 5: Inverse of Elasticity of Substitution Between STEM and College Non-STEM Workers ($1/\sigma_{sc}$)

	Census	Skills Based	Observations
Baseline	0.077 (0.082) [0.366]	0.050 (0.060) [0.416]	16
Efficiency Units	0.109 (0.114) [0.360]	0.063 (0.074) [0.407]	16
Hours as Supply	0.102 (0.082) [0.236]	0.073 (0.056) [0.213]	16
Pooled (Men & Women)	0.030 (0.085) [0.732]	0.014 (0.052) [0.792]	16
Pooled (Hours as Supply)	0.038 (0.094) [0.691]	0.023 (0.052) [0.660]	16

Source: IPUMS 5% 2000 Census and ACS 2000-2015. Newey-West heteroskedastic- and autocorrelation-consistent standard errors in parentheses; *p*-value reported in brackets. 'Census' column shows the result using Census 2010 STEM classification. 'Skill-Based' shows the result using Peri et al. (2015) top 4% skill-based STEM classification. The method of estimation is 2SLS using the labor supply of immigrant workers as an instrument for total labor supply. All regressions are weighted by the inverse of the sampling variance of the dependent variable.

Table 6: Inverse of Elasticity of Substitution Between High and Low Skilled ($1/\sigma_H$)

	Census	Skills Based	Observations
Baseline	-0.726	-0.734	16
	(0.238)	(0.242)	
	[0.009]	[0.010]	
Efficiency Units	-0.724	-0.728	16
	(0.237)	(0.237)	
	[0.009]	[0.009]	
Hours as Supply	-0.459	-0.457	16
	(0.098)	(0.096)	
	[0.000]	[0.000]	
Pooled (Men & Women)	-0.680	-0.685	16
	(0.235)	(0.237)	
	[0.013]	[0.013]	
Pooled (Hours as Supply)	-0.381	-0.378	16
	(0.062)	(0.060)	
	[0.000]	[0.000]	

Source: IPUMS 5% 2000 Census and ACS 2000-2015. Newey-West heteroskedastic- and autocorrelation-consistent standard errors in parentheses; p-value reported in brackets. 'Census' column shows the result using Census 2010 STEM classification. 'Skill-Based' shows the result using Peri et al. (2015) top 4% skill-based STEM classification. The method of estimation is 2SLS using the labor supply of immigrant workers as an instrument for total labor supply. All regressions are weighted by the inverse of the sampling variance of the dependent variable.

Table 7: Occupation Segregation of U.S. and Foreign-born Workers in STEM Sector in Year 2000

Age Group	*Less than Bachelor's Degree*	*Bachelor's Degree*	*Postgraduates*
28 - 32	0.12	0.20	0.29
33 - 37	0.10	0.15	0.27
38 - 42	0.12	0.12	0.25
42 - 47	0.13	0.16	0.24
48 - 52	0.14	0.16	0.27
52 - 57	0.13	0.19	0.26
58 - 62	0.17	0.20	0.29

Source: IPUMS 5% 2000 Census. The analysis used both men and women of age 28 to 62. STEM occupations are defined using Census 2010 STEM classification.

Table 8: Estimates of $(1/\sigma_{se})$ for Lower Education Group in STEM

	STEM		
	Census	Skill-Based	Observations
Baseline	0.074 (0.050) [0.136]	0.041 (0.059) [0.489]	48
Hours as Supply	0.067 (0.056) [0.230]	0.023 (0.073) [0.751]	48
Pooled (Men and Women)	0.041 (0.059) [0.489]	-0.019 (0.054) [0.724]	48
Pooled (Hours as Supply)	0.050 (0.053) [0.352]	-0.019 (0.054) [0.730]	48

Source: IPUMS 5% 2000 Census and ACS 2000-2015. Heteroskedastic- and cluster-robust standard errors at education groups in parentheses; *p*-value reported in brackets. 'Census' column shows the result using Census 2010 STEM classification. 'Skill-Based' shows the result using Peri et al. (2015) top 4% skill-based STEM classification. The method of estimation is 2SLS using the labor supply of immigrant workers as an instrument for total labor supply. All regressions are weighted by the inverse of the variance of the dependent variable.

Table 9: 2000-2015 Foreign STEM Supply Shocks and STEM Workers' Wages

	U.S.-born		Foreign-born	
	Without Externalities	*With Externalities*	*Without Externalities*	*With Externalities*
Panel A: 2000 - 2015 Estimates				
Less than Bachelor's Degree	1.75%	5.84%	0.71%	4.80%
Bachelor's Degree	0.54%	4.64%	-3.96%	0.13%
Post-graduates	-0.95%	3.14%	-5.66%	-1.56%
STEM Average	**0.58%**	**4.67%**	**-4.16%**	**-0.07%**
Panel B: H1-B Counterfactual Estimates				
Less than Bachelor's Degree	2.15%	7.11%	1.07%	6.02%
Bachelor's Degree	0.60%	5.56%	-5.05%	-0.09%
Post-graduates	-1.09%	3.87%	-6.74%	-1.78%
STEM Average	**0.71%**	**5.67%**	**-5.05%**	**-0.09%**

The wage effect is estimated using $\sigma_H = 2$, $\sigma_{sc} = \infty$, $\sigma_{se} = 6$, $\sigma_{sa} = 13$, $\sigma_{sn} = 18$, and actual wage shares in 2000 with pooled (men and women) sample. The wage effect in Panel A is calculated using the actual change in STEM immigrant supply in each cell from 2000 and 2015 holding the level of employment of non-STEM and U.S.-born STEM workers constant at their 2000 level. The wage effect in Panel B is calculated using the actual change in STEM immigrant supply in each cell from 2000 and 2015 plus the estimated additional number of STEM worker in the absence of H1-B Visa Reform Act of 2004 holding the level of employment of non-STEM and U.S.-born STEM workers constant at their 2000 level. 'Without Externalities' column assumes that STEM workers do not have an impact on TFP and Skill-biased tech. progress (i.e., ψ_A and ψ_B are set to be equal to zero).

Table 10: 2000-2015 Foreign STEM Supply Shocks and STEM Workers Wages - Assuming $\sigma_{sn} = \infty$

	All STEM Workers	
	Without Externalities	*With Externalities*
Panel A: 2000 - 2015 Estimates		
Less than Bachelor's Degree	1.67%	5.76%
Bachelor's Degree	-0.14%	3.95%
Post-graduates	-2.37%	1.72%
STEM Average	**-0.24%**	**3.85%**
Panel B: H1-B Counterfactual Estimates		
Less than Bachelor's Degree	2.06%	7.02%
Bachelor's Degree	-0.26%	4.70%
Post-graduates	-2.80%	2.16%
STEM Average	**-0.30%**	**4.66%**

The wage effect is estimated using $\sigma_H = 2$, $\sigma_{sc} = \infty$, $\sigma_{se} = 6$, $\sigma_{sa} = 13$, $\sigma_{sn} = \infty$,, and actual wage shares in 2000 with pooled (men and women) sample. The wage effect in Panel A is calculated using the actual change in STEM immigrant supply in each cell from 2000 and 2015 holding the level of employment of non-STEM and U.S.-born STEM workers constant at their 2000 level. The wage effect in Panel B is calculated using the actual change in STEM immigrant supply in each cell from 2000 and 2015 plus the estimated additional number of STEM worker in the absence of H1-B Visa Reform Act of 2004 holding the level of employment of non-STEM and U.S.-born STEM workers constant at their 2000 level. 'Without Externalities' column assumes that STEM workers do not have an impact on TFP and Skill-biased tech. progress (i.e., ψ_A and ψ_B are set to be equal to zero).

Table 11: 2000-2015 Foreign STEM Supply Shock and College Non-STEM/Low-skilled Wages

	Without Externalities	*With Externalities*
Panel A: 2000 - 2015 Estimates		
Low-skilled	0.60%	1.41%
College Non-STEM	-0.24%	3.85%
Panel B: H1-B Counterfactual Estimates		
Low-skilled	0.73%	1.71%
College Non-STEM	-0.30%	4.66%

The wage effect is estimated using $\sigma_H = 2$, $\sigma_{sc} = \infty$, and actual wage shares in 2000 with pooled (men and women) sample. The wage effect in Panel A is calculated using the actual change in STEM immigrant supply in each cell from 2000 and 2015 holding the level of employment of non-STEM and U.S.-born STEM workers constant at their 2000 level. The wage effect in Panel B is calculated using the actual change in STEM immigrant supply in each cell from 2000 and 2015 plus the estimated additional number of STEM worker in the absence of H1-B Visa Reform Act of 2004 holding the level of employment of non-STEM and U.S.-born STEM workers constant at their 2000 level. 'Without Externalities' column assumes that STEM workers do not have an impact on TFP and Skill-biased tech. progress (i.e., ψ_A and ψ_B are set to be equal to zero).

Table 12: Net Benefit/Loss of 2000-2015 Foreign STEM Supply Shock for U.S.-born Workers (in Billion USD)

	Without Externalities		With Externalities	
	$\sigma_{sn} = 18$	$\sigma_{sn} = \infty$	$\sigma_{sn} = 18$	$\sigma_{sn} = \infty$
STEM Workers				
Less than Bachelor's Degree	1.70	1.61	5.66	5.58
Bachelor's Degree	0.66	-0.18	5.64	4.79
Post-graduates	-0.67	-1.70	2.23	1.20
Benefit/Loss for Native STEM	*1.69*	*-0.27*	*13.53*	*11.58*
College Non-STEM and Low Skilled				
Natives College Non-STEM	-4.97	-4.97	78.04	78.04
Low-skilled Natives	4.93	4.93	11.62	11.62
Net Benefit/Loss	**1.64**	**-0.31**	**103.19**	**101.24**
As % of GDP in 1999	**0.02%**	**0.00%**	**1.03%**	**1.01%**

The net benefit is estimated by using the annual earnings of all workers (men and women) who reported positive earnings and worked at least a week. The benefit/losses in each skill group is calculated by multiplying the average earnings in a group with its estimated wage effect and the number of workers in the group. The benefit/loss in each skill group can then be summed up to get the overall benefit/loss by education level. 'Without Externalities' column assumes that STEM workers do not have an impact on TFP and Skill-biased tech. progress (i.e., ψ_A and ψ_B are set to be equal to zero).

Table 13: Net Benefit/Loss of 2000-2015 Foreign STEM Supply Shock for U.S.-born Workers Under H1-B Counterfactual Estimates (in Billion USD)

	Without Externalities		With Externalities	
	$\sigma_{sn} = 18$	$\sigma_{sn} = \infty$	$\sigma_{sn} = 18$	$\sigma_{sn} = \infty$
STEM Workers				
Less than Bachelor's Degree	2.08	2.00	6.89	6.80
Bachelor's Degree	0.73	-0.32	6.77	5.71
Post-graduates	-0.77	-1.99	2.75	1.53
Benefit/Loss for Native STEM	*2.04*	*-0.31*	*16.40*	*14.05*
College Non-STEM and Low Skilled				
Natives College Non-STEM	-6.02	-6.02	94.58	94.58
Low-skilled Natives	5.97	5.97	14.08	14.08
Net Benefit	**1.99**	**-0.36**	**125.06**	**122.71**
As % of GDP in 1999	**0.02%**	**0.00%**	**1.25%**	**1.23%**

The net benefit is estimated by using the annual earnings of all workers (men and women) who reported positive earnings and worked at least a week. The benefit/losses in each skill group is calculated by multiplying the average earnings in a group with its estimated wage effect and the number of workers in the group. The benefit/loss in each skill group can then be summed up to get the overall benefit/loss by education level. 'Without Externalities' column assumes that STEM workers do not have an impact on TFP and Skill-biased tech. progress (i.e., ψ_A and ψ_B are set to be equal to zero).

Figure 1: STEM Sector Characteristics Over Time

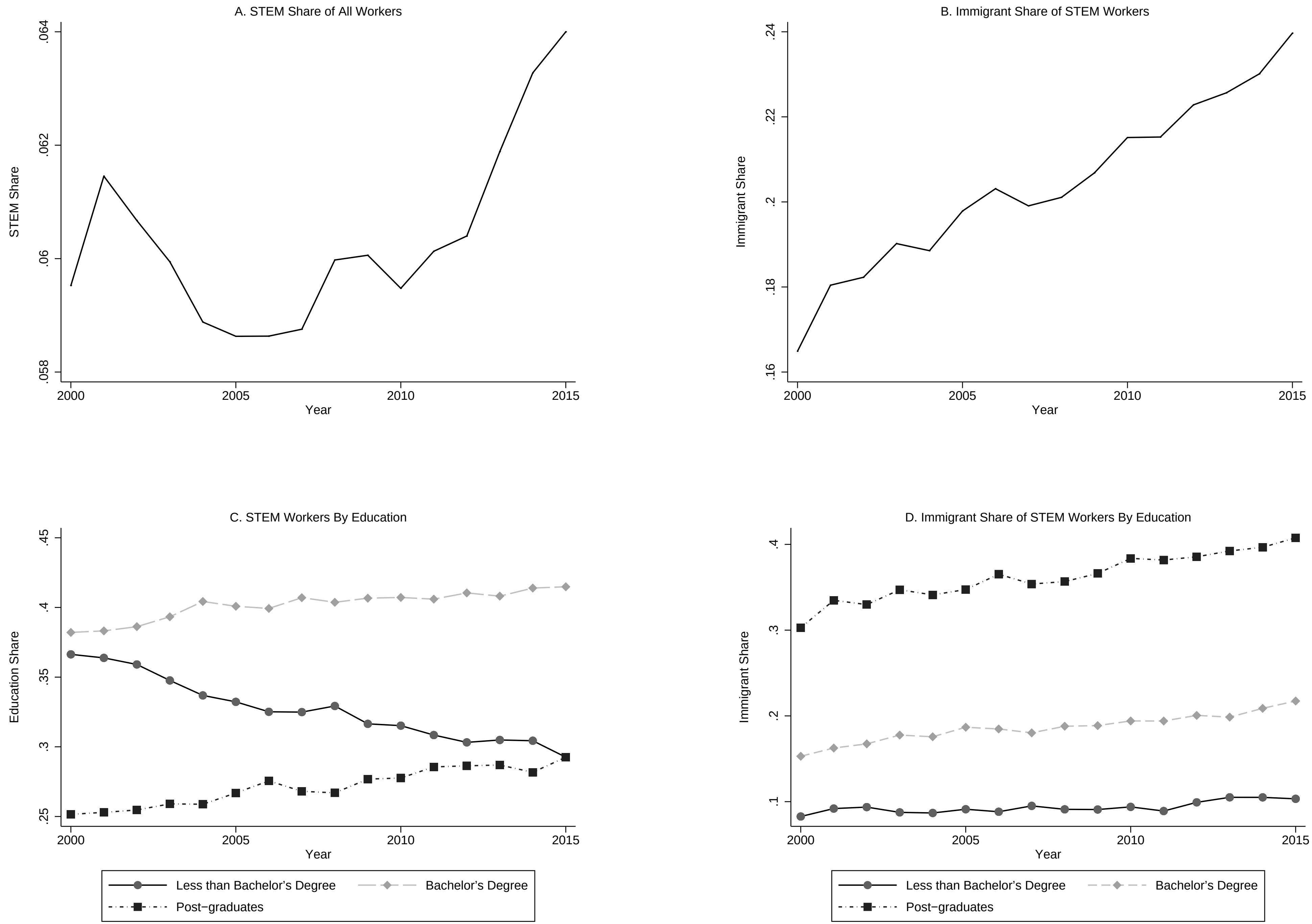


Figure 2: Old and Young Wages in STEM

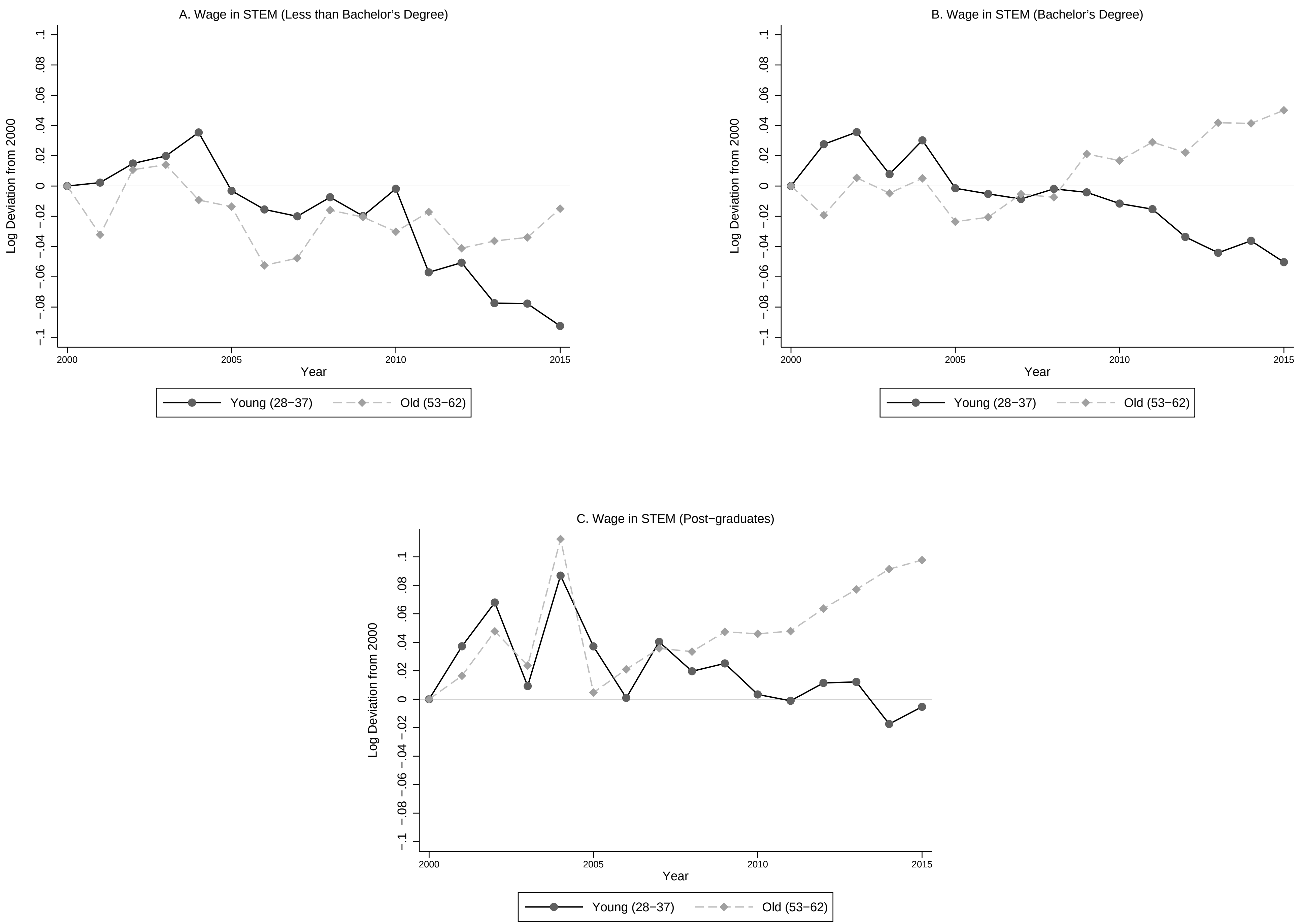
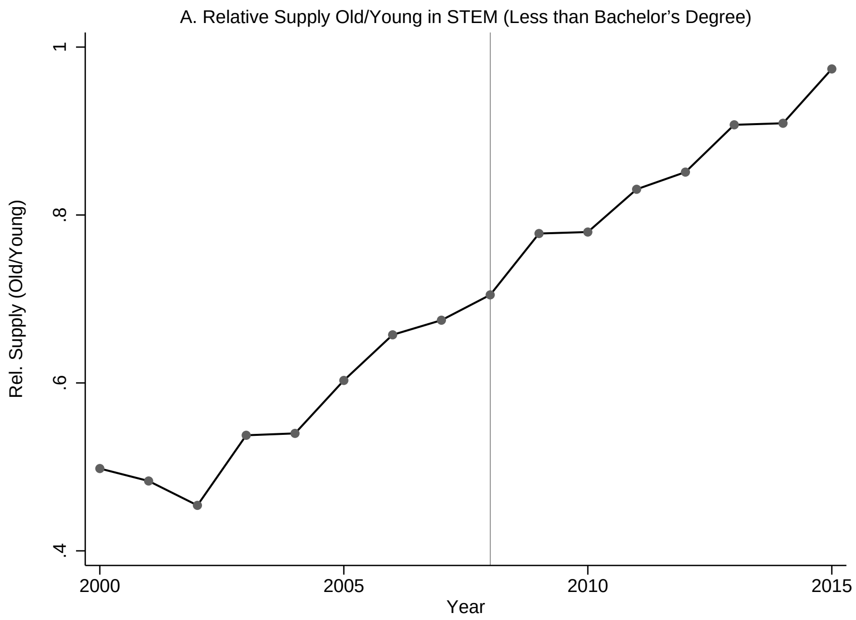
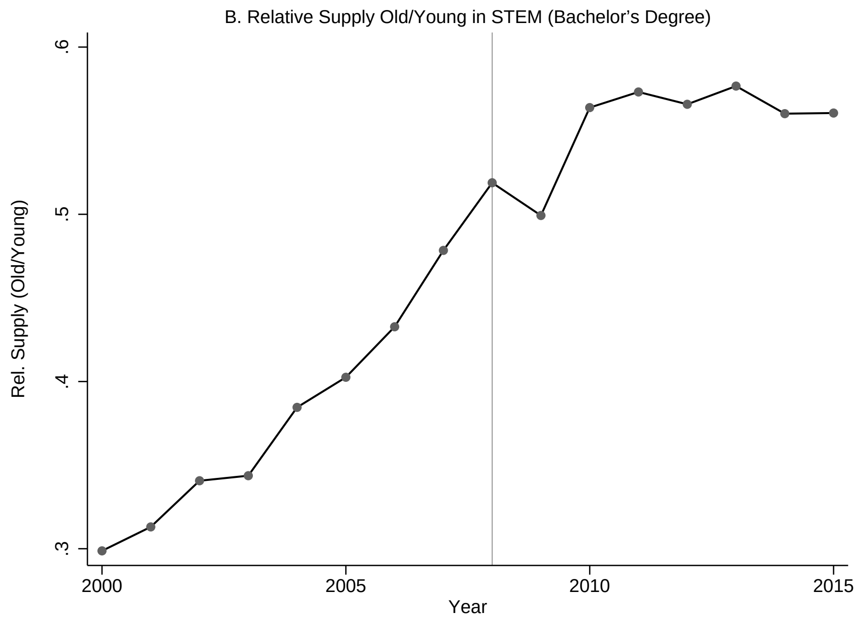


Figure 3: Relative Supply Old/Young in STEM





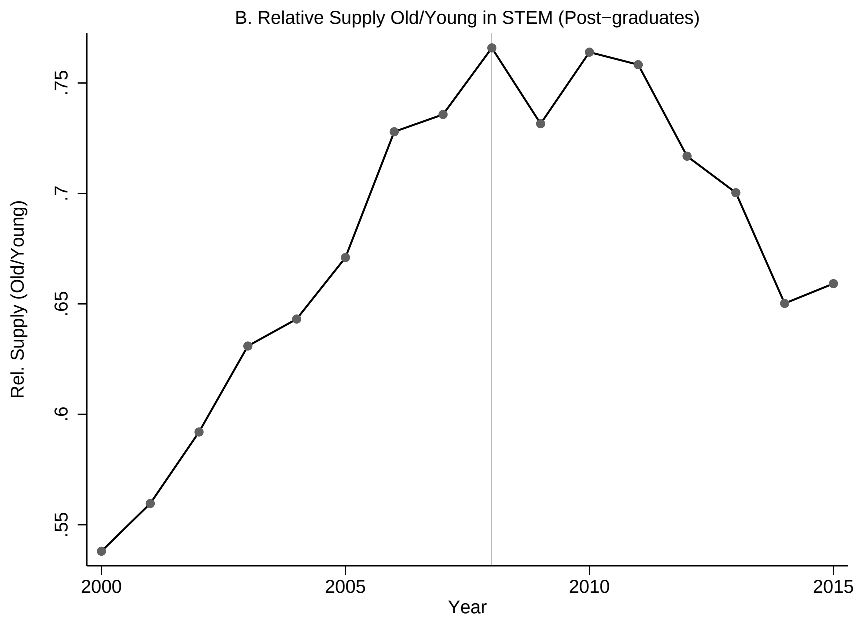


Figure 4: 2000-2015 Foreign STEM Supply Shock and Native STEM Workers' Wages With Externalities Effect

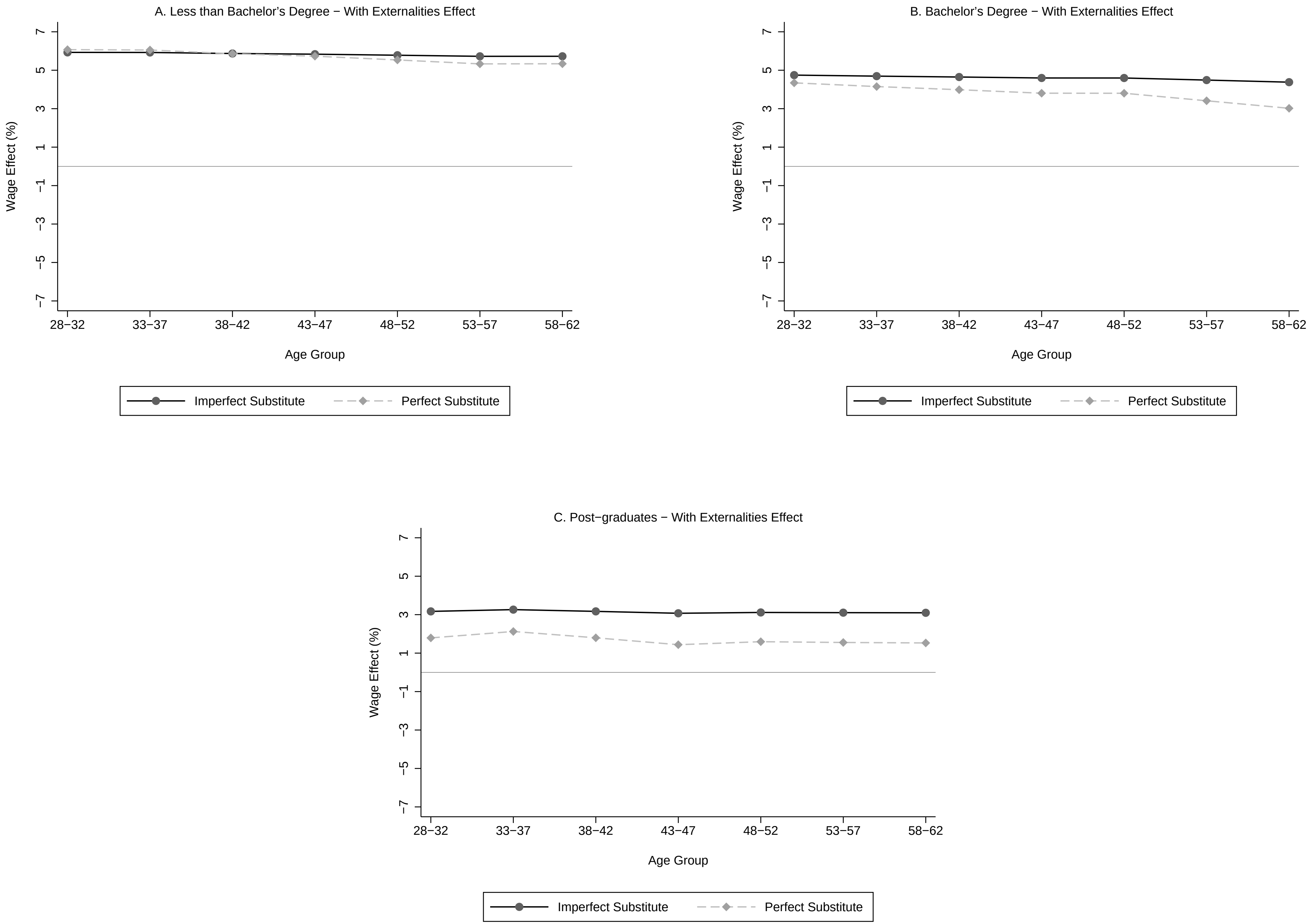


Figure 5: 2000-2015 Foreign STEM Supply Shock and Immigrant STEM Workers' Wages with Spillover Effects

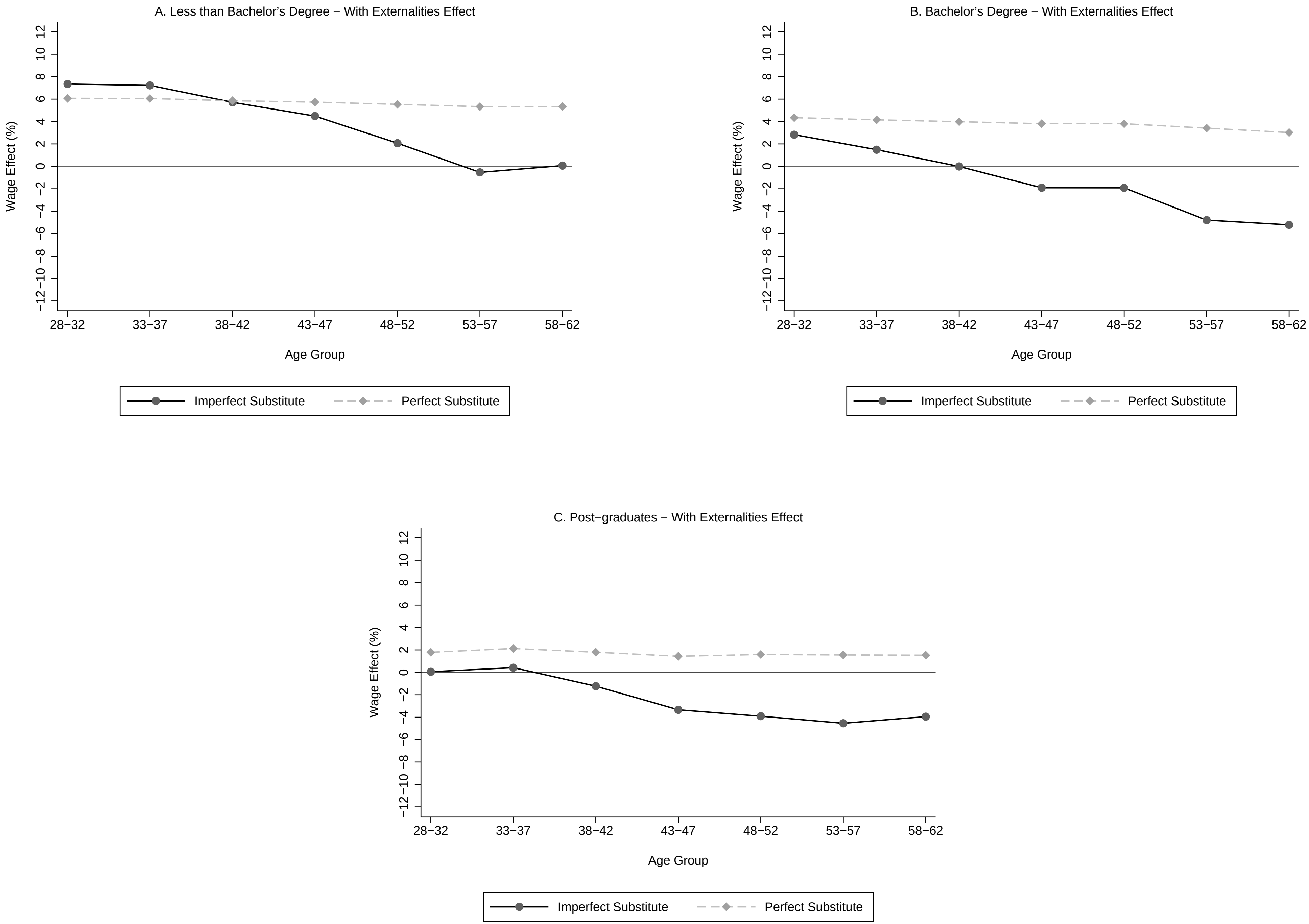


Figure 6: Counterfactual H-1B Simulation and U.S.-born STEM Workers' Wages with Spillover Effects

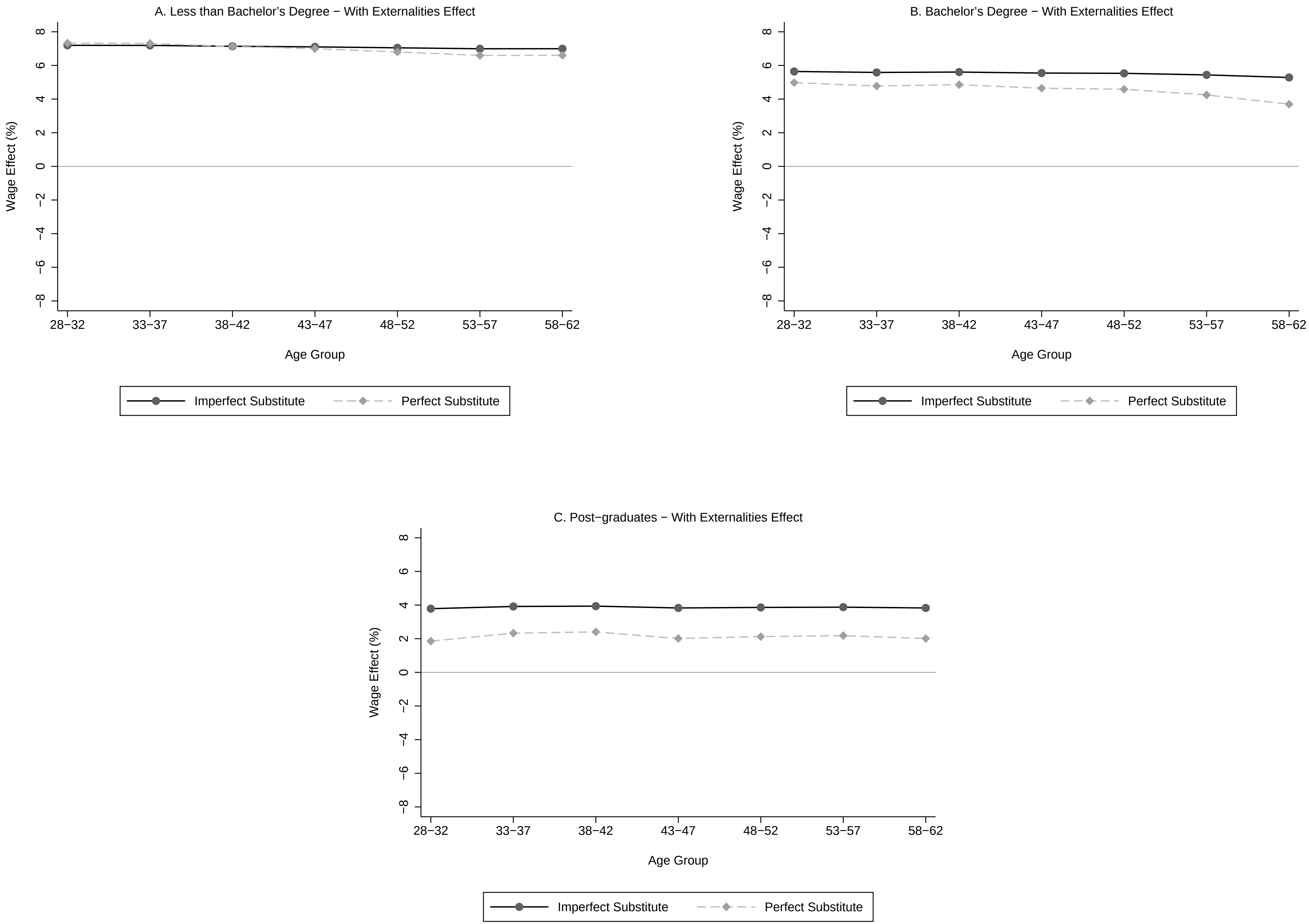
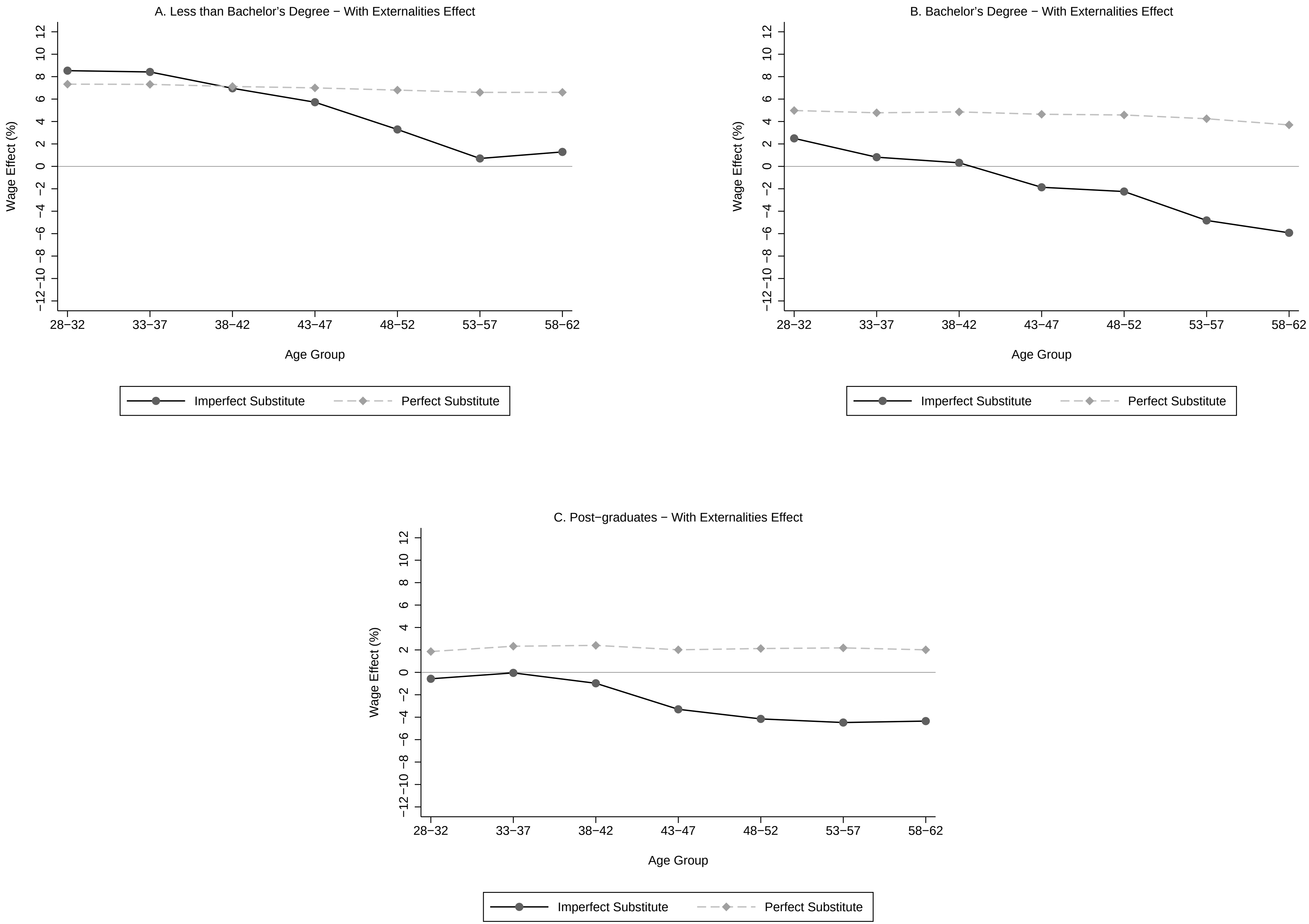


Figure 7: Counterfactual H-1B Simulation and Immigrants STEM Workers' Wages with Spillover Effects



References

Bohn, S., Lofstrom, M., and Raphael, S. (2015). Do e-verify mandates improve labor market outcomes of low-skilled native and legal immigrant workers? *Southern Economic Journal*, 81(4):960–979.

Bonin, H. (2005). Wage and employment effects of immigration to germany: Evidence from a skill group approach. *Institute for the Study of Labor Discussion Paper No. 1875*.

Borjas, G. J. (1980). The relationship between wages and weekly hours of work: The role of division bias. *The Journal of Human Resources*, 15(3):409–423.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The quarterly journal of economics*, 118(4):1335–1374.

Borjas, G. J. (2014). *Immigration economics*. Harvard University Press.

Borjas, G. J. (2017). The wage impact of the marielitos: A reappraisal. *ILR Review*, 70(5):1077–1110.

Borjas, G. J. and Doran, K. B. (2012). The collapse of the soviet union and the productivity of american mathematicians. *The Quarterly Journal of Economics*, 127(3):1143–1203.

Borjas, G. J., Grogger, J., and Hanson, G. H. (2008). Imperfect substitution between immigrants and natives: a reappraisal. Technical report, National Bureau of Economic Research.

Borjas, G. J., Grogger, J., and Hanson, G. H. (2012). Comment: On estimating elasticities of substition. *Journal of the European Economic Association*, 10(1):198–210.

Borjas, G. J. and Katz, L. F. (2007). The evolution of the mexican-born workforce in the united states. In *Mexican immigration to the United States*, pages 13–56. University of Chicago Press.

Bound, J., Khanna, G., and Morales, N. (2017). Understanding the economic impact of the h-1b program on the us. In *High-Skilled Migration to the United States and its Economic Consequences*. University of Chicago Press.

Bratsberg, B. and Raaum, O. (2012). Immigration and wages: Evidence from construction. *The Economic Journal*, 122(565):1177–1205.

Bratsberg, B., Raaum, O., Røed, M., and Schøne, P. (2014). Immigration wage effects by origin. *The Scandinavian Journal of Economics*, 116(2):356–393.

Burtless, G. (2013). The impact of population aging and delayed retirement on workforce productivity. *Available at: https://ssrn.com/abstract=2275023*.

Card, D. (1990). The impact of the mariel boatlift on the miami labor market. *ILR Review*, 43(2):245–257.

Card, D. and Lemieux, T. (2001). Can falling supply explain the rising return to college for younger men? a cohort-based analysis. *The Quarterly Journal of Economics*, 116(2):705–746.

Chiswick, B. R. (1978). The effect of americanization on the earnings of foreign-born men. *Journal of political Economy*, 86(5):897–921.

Doran, K., Gelber, A., and Isen, A. (2016). The effects of high-skilled immigration policy on firms: Evidence from visa lotteries1. *Working Paper*.

Dustmann, C., Frattini, T., and Preston, I. P. (2013). The effect of immigration along the distribution of wages. *The Review of Economic Studies*, 80(1):145–173.

Hunt, J. and Gauthier-Loiselle, M. (2010). How much does immigration boost innovation? *American Economic Journal: Macroeconomics*, 2(2):31–56.

Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The quarterly journal of economics*, 107(1):35–78.

Kerr, S. P., Kerr, W. R., and Lincoln, W. F. (2015). Skilled immigration and the employment structures of us firms. *Journal of Labor Economics*, 33(S1):S147–S186.

Kerr, W. R. and Lincoln, W. F. (2010). The supply side of innovation: H-1b visa reforms and us ethnic invention. *Journal of Labor Economics*, 28(3):473–508.

Langdon, D., McKittrick, G., Beede, D., Khan, B., and Doms, M. (2011). Stem: Good jobs now and for the future. esa issue brief# 03-11. *US Department of Commerce*.

Lin, J. (2011). Technological adaptation, cities, and new work. *Review of Economics and Statistics*, 93(2):554–574.

Manacorda, M., Manning, A., and Wadsworth, J. (2012). The impact of immigration on the structure of wages: theory and evidence from britain. *Journal of the European Economic Association*, 10(1):120–151.

Moser, P., Voena, A., and Waldinger, F. (2014). German jewish émigrés and us invention. *The American Economic Review*, 104(10):3222–3255.

National Science Board (2016). Science and engineering indicators. *National Science Foundation*.

Orrenius, P. M. and Zavodny, M. (2015). The impact of e-verify mandates on labor market outcomes. *Southern Economic Journal*, 81(4):947–959.

Ottaviano, G. I. and Peri, G. (2012). Rethinking the effect of immigration on wages. *Journal of the European economic association*, 10(1):152–197.

Peri, G., Shih, K., and Sparber, C. (2015). Stem workers, h-1b visas, and productivity in us cities. *Journal of Labor Economics*, 33(S1):S225–S255.

Peri, G. and Sparber, C. (2009). Task specialization, immigration, and wages. *American Economic Journal: Applied Economics*, 1(3):135–169.

Peri, G. and Sparber, C. (2011). Highly educated immigrants and native occupational choice. *Industrial Relations: a journal of economy and society*, 50(3):385–411.

Peri, G. and Yasenov, V. (2018). The labor market effects of a refugee wave: Synthetic control method meets the mariel boatlift. *Journal of Human Resources*, page 0217_8561R1.

Ruggles, S., Genadek, K., Goeken, R., Grover, J., and Sobek, M. (2015). Integrated public use microdata series: Version 6.0 [machine-readable database]. *Minneapolis: University of Minnesota*.

Steinhardt, M. F. (2011). The wage impact of immigration in germany-new evidence for skill groups and occupations. *The BE Journal of Economic Analysis & Policy*, 11(1).

USCIS (2004). Characteristics of h-1b specialty occupation workers. *https://www.uscis.gov/tools/reports-studies/reports-and-studies*.

USCIS (2017). Understanding h-1b requirement. *https://www.uscis.gov/working-united-states/temporary-workers/h-1b-specialty-occupations-dod-cooperative-research-and-development-project-workers-and-fashion-models*.

Appendix A

The components of equation (9) to (12) can be calculated in the following way:

$$d \ln S_{ea} = \frac{\theta^I_{sea} I^\eta_{sea}}{\theta^I_{sea} I^\eta_{sea} + \theta^N_{sea} N^\eta_{sea}} d \ln I_{sea} = \alpha^I_{sea} d \ln I_{sea}$$

where α^I_{sea} is the share of labor income of foreign born STEM workers in education-age cell. Similarly for $d \ln S_e$:

$$d \ln S_e = \sum_a \frac{\theta_{sea} S^\lambda_{ea}}{\sum_a \theta_{sea} S^\lambda_{ea}} d \ln S_{ea} = \sum_a \alpha_{sea} d \ln S_{ea}$$

where α_{sea} is the share of labor income of STEM workers of age group a within education group e. Now, I can calculate $d \ln S$:

$$d \ln S = \sum_e \frac{\theta_{se} S^\pi_e}{\sum_e \theta_{se} S^\pi_e} d \ln S_e = \sum_e \alpha_{se} d \ln S_e$$

where α_{se} is the share of labor income of STEM workers with education e. Then, I have

$$d \ln H = \frac{\gamma S^\mu}{\gamma S^\mu + (1-\gamma) C^\mu} d \ln S = \alpha_s d \ln S$$

where α_s is the share of labor income of STEM workers in the high skilled group. Finally, I have

$$d \ln Y = \frac{\beta H^\rho}{\beta H^\rho + (1-\beta) L^\rho} d \ln H = \alpha_H d \ln H$$

where α_H is the share of labor income of high-skilled workers. For spillover effects, note that I can approximate ψ_A as follows:

$$\psi_A = \frac{\Delta A}{\Delta S}\frac{S}{A} = \phi_A \frac{S}{E}$$

where $\phi_A = \frac{\Delta A}{\Delta S}\frac{E}{A}$. Similarly for ψ_B:

$$\psi_B = \frac{\Delta \beta}{\Delta S}\frac{S}{\beta} = \phi_B \frac{S}{E}$$

where $\phi_B = \frac{\Delta \beta}{\Delta S}\frac{E}{\beta}$. I obtained estimates of ϕ_A and ϕ_B from Peri et al. (2015), which are 3.61 and 1.64 respectively. As STEM employment share in 2000 based on Census' STEM classification is approximately 6%, I used the value of 0.22 and 0.10 for ψ_A and ψ_B respectively. The estimate of ψ_A is close to the Bound et al. (2017) estimate of increase in TFP in the IT sector that is contributed to the number of computer scientists in the sector (0.233). To get percentage change in average wages by groups, I follow Ottaviano and Peri (2012) by weighting the percentage changes by wage bill shares.

Appendix B

Appendix Table 1: STEM Classifications

Census 2010 STEM List	Peri et al. (2015) Top 4% Skill-Based STEM List
Actuaries	Actuaries
Aerospace Engineers	Aerospace Engineer
Agricultural and Food Science Technicians	Agricultural and Food Scientists
Agricultural and Food Scientists	Biological Scientists
Architectural and Engineering Managers	Chemical Engineers
Astronomers and Physicists	Chemists
Atmospheric and Space Scientists	Civil Engineers
Biological Scientists	Computer Software Developers
Biological Technicians	Computers Systems Analysts and Computer Scientists
Chemical Engineers	Economist, Market Researchers, and Survey Researchers
Chemical Technicians	Electrical Engineer
Chemists and Materials Scientists	Engineering Technician, n.e.c.
Civil Engineers	Geologists
Computer and Information Systems Managers	Industrial Engineers
Computer Hardware Engineers	Mathematicians and Mathematical Scientists
Computer Programmers	Mechanical Engineers
Computer Scientists and Systems Analysts/Network systems Analysts/Web Developers	Medical Scientists
Computer Support Specialists	Metallurgical and Materials Engineers, variously phrased
Conservation Scientists and Foresters	Not-elsewhere-classified Engineers
Database Administrators	Operations and Systems Researchers and Analysts
Drafters	Optometrists
Economists and market researchers	Petroleum, Mining, and Geological Engineers
Electrical and Electronics Engineers	Physical Scientists, n.e.c.
Engineering Technicians, Except Drafters	Physicists and Astronomers
Engineers, nec	Podiatrists
Environmental Engineers	Programmers of numerically controlled machine tools
Environmental Scientists and Geoscientists	Sales Engineers
Geological and Petroleum Technicians, and Nuclear Technicians	Surveyors, Cartographers, Mapping Scientists and Technicians
Industrial Engineers, including Health and Safety	
Life, Physical, and Social Science Technicians, nec	
Marine Engineers and Naval Architects	
Materials Engineers	
Mathematical science occupations, nec	
Mechanical Engineers	
Medical Scientists, and Life Scientists, All Other	
Natural Science Managers	
Network and Computer Systems Administrators	
Operations Research Analysts	
Petroleum, mining and geological engineers, including mining safety engineers	
Physical Scientists, nec	
Psychologists	
Sales Engineers	
Social Scientists, nec	
Software Developers, Applications and Systems Software	
Surveying and Mapping Technicians	
Surveyors, Cartographers, and Photogrammetrists	
Urban and Regional Planners	