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Essays on the Socio-Economic Impacts of Immigration in the United States

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by

Christian Gunadi

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Chapter 1, "An Inquiry Into the Impact of Highly-skilled STEM Immigration on the U.S. Economy," has been published in Labour Economics and is available at: https://doi.org/10.1016/j.labeco.2019.101751. Chapter 2, "On the Association Between Undocumented Immigration and Crime in the United States," has been published in Oxford Economic Papers and is available at: https://doi.org/10.1093/oep/gpz057. Chapter 3, "Immigration and the Health of U.S. Natives," has been published in Southern Economic Journal and is available at: https://doi.org/10.1002/soej.12425.

To sunny, beautiful days in Riverside

ABSTRACT OF THE DISSERTATION

Essays on the Socio-Economic Impacts of Immigration in the United States

by

Christian Gunadi

Doctor of Philosophy, Graduate Program in Economics
University of California, Riverside, June 2020
Dr. Joseph Cummins, Chairperson

This dissertation is an attempt to extend our understanding of how a country may benefit from immigration as well as to examine the potential costs associated with immigration. The first chapter, "An Inquiry Into the Impact of Highly-skilled STEM Immigration on the U.S. Economy," examines whether foreign STEM workers displace or complement U.S.-born STEM workers and the potential benefit of high-skilled immigration. An important finding obtained from the analysis is that similarly skilled U.S. and foreign-born STEM workers are imperfect substitutes, implying that it is relatively hard for U.S. firms to fully replace its native STEM workers with their foreign-born counterparts. It is also estimated that STEM immigration from 2000 to 2015 yields approximately 103 billion USD (1.03% of U.S. GDP in 1999) benefit for U.S.-born workers.

Although immigration has benefits, there may be costs associated with admitting more immigrants into the country. In particular, there are concerns that undocumented immigration may lead to higher crime rates. The second chapter, "On the Association Between Undocumented Immigration and Crime in the United States," examines whether this is the case. The main findings suggest that overall violent and property crime rates across the U.S. states are not statistically significantly increase by unauthorized immigration.

The final chapter, "Immigration and the Health of United States Natives," examines the relationship between immigration and the health of the native population in the

United States. There are two competing forces in which immigration may affect the health of U.S.-born individuals. On the one hand, immigration may put a strain on the health care system, adversely impacting the health of the native population. On the other hand, immigration could nudge native workers from risk-intensive, physically demanding jobs towards occupations that require more communication and interactive ability, potentially improving their health. The main findings fail to show that immigration adversely affects the health of U.S. natives. Instead, it suggests that the presence of low-skilled immigrants may improve the health of low-skilled U.S.-born individuals.

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Chapter 1

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

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 1.1). 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 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 1.1).[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

[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.

[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 1.1. 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).

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.

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.

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, 2017c; 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).[3] A closely related study is the work by Turner (2017) who found that the wages of STEM workers fell by approximately 4 to 12 percent relative to non-STEM because of immigration from 1990 to 2010. The work by Turner (2017), however, did not allow for the imperfect substitutability between similarly skilled U.S.- and foreign-born STEM workers. Furthermore, Turner (2017) did not take into account that the inflow of immigrant STEM workers has positive productivity effects. This paper complements the findings by Turner (2017) and other related studies in two important ways. First, this paper analyzes the degree of substitutability between similarly skilled U.S.- and foreign-born STEM workers, which have not been examined previously in the literature to my knowledge. The finding of imperfect substitutability between these two types of workers is important because it implies that the adverse effect of STEM immigration would be largely felt among immigrant STEM workers themselves. Additionally, it also implies that the finding in Kerr and Lincoln (2010) and Peri et al. (2015), who found that the wages and employment of U.S.-born workers are not adversely affected by the inflow of H-1B STEM workers, can be partly explained by the imperfect substitutability between U.S.- and foreign-born STEM workers. Another important contribution of this paper is that it examines how much the relative wages within STEM are affected by STEM immigration. As noted by Kerr and Turner (2015), there is a need to understanding how much the wages within the STEM sector are affected by STEM immigration, especially since the flow of immigrant STEM workers are not uniform across skill groups.

The rest of the paper is constructed as follows. Section 1.1 describes the theoretical framework. Section 1.2 describes the data used in the analysis. Section 1.3 and 1.4 present the estimation of the parameters used to simulate the wage effect of STEM immigration. Section 1.5 documents the results of the analysis. Section 1.6 concludes.

[3] Another related study is by Kerr et al. (2015) who found that an increase in the skilled H-1B immigrant workers in a firm is associated with a rising employment of skilled workers, especially for young natives.

1.1 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:[4]

$$Y_t = \left\{ A(S_t)\left[\beta(S_t)H_t^{\rho} + (1-\beta(S_t))L_t^{\rho}\right]\right\}^{\frac{1}{\rho}} \tag{1.1}$$

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 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 workers of all levels of educational attainment and non-STEM college-educated workers:

$$H_t = [\gamma_t S_t^{\mu} + (1-\gamma_t)C_t^{\mu}]^{\frac{1}{\mu}} \tag{1.2}$$

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

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:

$$S_t = [\sum_e \theta_{set} S_{et}^{\pi}]^{\frac{1}{\pi}} \tag{1.3}$$

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:

$$S_{et} = [\sum_a \theta_{seat} S_{eat}^{\lambda}]^{\frac{1}{\lambda}} \tag{1.4}$$

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:

$$S_{eat} = [\theta^N_{seat} N^{\eta}_{seat} + \theta^I_{seat} I^{\eta}_{seat}]^{\frac{1}{\eta}} \tag{1.5}$$

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^N_{seat} and θ^I_{seat} are the relative efficiency of U.S. and foreign-born STEM workers with education e and age a. Without loss of generality, I assume $\theta^N_{seat} + \theta^I_{seat} = 1$. 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):

$$\begin{aligned}\ln W^i_{seat} = {} & \frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln\beta_t + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})\ln H_t + \ln\gamma_t + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}})\ln S_t + \ln\theta_{set} + \\ & + (\frac{1}{\sigma_{sa}} - \frac{1}{\sigma_{se}})\ln S_{et} + \ln\theta_{seat} + (\frac{1}{\sigma_{sn}} - \frac{1}{\sigma_{sa}})\ln S_{eat} + \ln\theta^i_{seat} - \frac{1}{\sigma_{sn}}\ln i_{seat}\end{aligned} \tag{1.6}$$

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:

$$\ln W^c_t = \frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln\beta_t + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})\ln H_t + \ln\gamma_t - \frac{1}{\sigma_{sc}}\ln C_t \tag{1.7}$$

$$\ln W^L_t = \frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln(1-\beta_t) - \frac{1}{\sigma_H}\ln L_t \tag{1.8}$$

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:[5]

$$\begin{aligned} d\ln W^N_{sea} = \frac{1}{\sigma_H}d\ln Y + \psi_A d\ln S + \psi_B d\ln S + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})d\ln H + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}})d\ln S + \\ + (\frac{1}{\sigma_{sa}} - \frac{1}{\sigma_{se}})d\ln S_e + (\frac{1}{\sigma_{sn}} - \frac{1}{\sigma_{sa}})d\ln S_{ea} \end{aligned} \tag{1.9}$$

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 education e and age a is

$$\begin{aligned} d\ln W^I_{sea} = \frac{1}{\sigma_H}d\ln Y + \psi_A d\ln S + \psi_B d\ln S + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})d\ln H + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}})d\ln S + \\ + (\frac{1}{\sigma_{sa}} - \frac{1}{\sigma_{se}})d\ln S_e + (\frac{1}{\sigma_{sn}} - \frac{1}{\sigma_{sa}})d\ln S_{ea} - \frac{1}{\sigma_{sn}}d\ln I_{sea} \end{aligned} \tag{1.10}$$

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.[6] 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.

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

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

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 STEM workers are ignored (i.e., when S is held constant, it follows that the externalities effects – ψ_A and ψ_B – are omitted).[7] 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 can be written as:

$$d\ln W^c = \frac{1}{\sigma_H} d\ln Y + \psi_A d\ln S + \psi_B d\ln S + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H}) d\ln H \tag{1.11}$$

$$d\ln W^L = \frac{1}{\sigma_H} d\ln Y + \psi_A d\ln S - \frac{\beta}{1-\beta}\psi_B d\ln S \tag{1.12}$$

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.

[7] 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.

1.2 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 of full-time workers who are not self-employed or currently in school.[8] 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.[9] 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).[10]

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.[11]

In regression analysis to obtain elasticity parameter estimates that were necessary

[8]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.

[9]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.

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

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

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.[12] This is because women's labor supply is more likely to 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.[13] 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).[14] 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

[12]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.

[13]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.

[14]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.

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 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.[15] Unless otherwise specified, the analysis used Census 2010 STEM occupations classification. The list of STEM occupations is provided in Table 1.12 in the Appendix.

1.3 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 σ_{sn} 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 is worth noting 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

[15] 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.

iteratively and present the results obtained using the actual number of workers and CES-weighted labor aggregate.

1.3.1 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):

$$\ln \frac{W^I_{seat}}{W^N_{seat}} = \ln \frac{\theta^I_{seat}}{\theta^N_{seat}} - \frac{1}{\sigma_{sn}} \ln \frac{I_{seat}}{N_{seat}} \tag{1.13}$$

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:

$$\ln \frac{\theta^I_{seat}}{\theta^N_{seat}} = \delta_t + \delta_{ea} + \delta_{et} + \delta_{at} \tag{1.14}$$

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

$$\ln \frac{W^I_{seat}}{W^N_{seat}} = \delta_t + \delta_{ea} + \delta_{et} + \delta_{at} - \frac{1}{\sigma_{sn}} \ln \frac{I_{seat}}{N_{seat}} \tag{1.15}$$

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}.

1.3.2 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

$$\ln W_{seat} = \underbrace{\frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln\beta_t + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})\ln H_t + \ln\gamma_t + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}})\ln S_t}_{\delta_t}$$
$$+ \underbrace{\ln\theta_{set} + (\frac{1}{\sigma_{sa}} - \frac{1}{\sigma_{se}})\ln S_{et}}_{\delta_{et}} + \ln\theta_{seat} - \frac{1}{\sigma_{sa}}\ln S_{eat} \quad (1.16)$$

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:

$$\ln\theta_{seat} = \delta_{ea} + \delta_{at} \quad (1.17)$$

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 (1.2) and (1.3) show the evolution of wages between older and young STEM workers since 2000.[16] 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 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

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

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 1.3). 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.[17] Therefore, to obtain an estimate of σ_{sa}, I estimate the following:

$$\ln W_{seat} = \delta_t + \delta_{et} + \delta_{ea} + \delta_{at} - \frac{1}{\sigma_{sa}} \ln S_{eat} \tag{1.18}$$

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 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}.

[17] 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.

1.3.3 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

$$\ln W_{set} = \underbrace{\frac{1}{\sigma_H}\ln Y_t + \ln A_t + \ln\beta_t + (\frac{1}{\sigma_{sc}} - \frac{1}{\sigma_H})\ln H_t + \ln\gamma_t + (\frac{1}{\sigma_{se}} - \frac{1}{\sigma_{sc}})\ln S_t +}_{\delta_t} \\ + \ln\theta_{set} - \frac{1}{\sigma_{se}}\ln S_{et} \quad (1.19)$$

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:

$$\ln W_{set} = \delta_t + \delta_e + lineartrend \times \delta_e - \frac{1}{\sigma_{se}}\ln S_{et} \quad (1.20)$$

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.

1.3.4 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:

$$\ln\frac{W_{st}}{W_{ct}} = \ln\frac{\gamma_t}{(1-\gamma_t)} - \frac{1}{\sigma_{sc}}\ln\frac{S_t}{C_t} \quad (1.21)$$

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:

$$\ln \frac{W_{st}}{W_{ct}} = lineartrend - \frac{1}{\sigma_{sc}} \ln \frac{S_t}{C_t} \tag{1.22}$$

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).

1.3.5 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:

$$\ln \frac{W_t^H}{W_t^L} = \ln \frac{\beta_t}{(1-\beta_t)} - \frac{1}{\sigma_H} \ln \frac{H_t}{L_t} \tag{1.23}$$

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

1.4 Estimates of Elasticity of Substitution

1.4.1 Estimate of σ_{sn}

Table 1.2 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 1.2 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.[18] I took the most conservative value ($\sigma_{sn} = 18$) 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.[19] Peri and Sparber (2009) argued that immigrants 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

[18]As an additional analysis, I check whether the estimates are robust to a stricter Census STEM classification that excludes STEM technician occupations which may not be closely related to innovation and technological progress usually associated with STEM workers. The results of the analysis are similar and reported on Appendix Table 1.13. The excluded occupations are "Agricultural and Food Science Technicians", "Biological Technicians", "Chemical Technicians", "Geological and Petroleum Technicians, Nuclear Technicians", "Life, Physical, and Social Science Technicians, nec", "Engineering Technicians, Except Drafters", and "Surveying and Mapping Technicians". Considering that the typical H-1B immigrants are more likely to be young, I also check whether this result holds if I limit the sample only to those of age 28 to 32 years old. The result does hold and reported on Appendix Table 1.14.

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

analytical skills, while their U.S.-born counterparts specialize in occupations requiring communication and interactive skills. Further suggesting specialization within STEM, a recent report by Ortega and Sparber (2016) found that among STEM graduates, immigrants are more likely to acquire a degree in engineering, computer science, mathematics or physics, while natives are more likely to pursue biological science and psychology.

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 1.3). 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. A more intuitive way to see if there is specialization between U.S- and foreign-born workers within STEM is by taking a look at the share of immigrants across occupations within STEM. Since immigrants constitute approximately 16% of the workforce within STEM, the share of immigrants across occupations within STEM should be around 16% if there is no task specialization between immigrant and U.S-born in STEM. However, this is not the case (Appendix Table 1.15). Immigrants are overrepresented in Physical Sciences occupations, while they are underrepresented in Psychology as well as Computer, Engineering and Natural Sciences Manager occupations. Within Engineering, foreign-born workers are overrepresented in Computer Hardware Engineers occupations, while they are underrepresented in Sales Engineer occupations, which require higher communication and interactive skills.

To further examine the task specialization within the STEM sector, I obtain the required mathematics and speaking skill level for each occupation from the U.S. Department of Labor O*Net survey. Then, I crosswalk the O*Net 2010 SOC code with Census 2010 SOC code from IPUMS, which is used in ACS 2010-2015. After merging it with the individual level data in ACS 2010-2015, it follows that each individual in the sample have mathematics and speaking skill values associated with his/her occupation.[20] In Appendix

[20] O*Net scales the skill level required for each occupation on a scale ranging from 0 to 7. Higher value

Table 1.16, I report the descriptive statistics for both immigrants and U.S. natives on the average mathematics and speaking skill level associated with their occupations. The results suggest that immigrants are more likely to be employed in occupations requiring higher mathematics skill in the STEM sector, in line with Peri and Sparber (2011) who found that immigrants with graduate degrees specialize in occupations that require more quantitative skills. Comparing the magnitude of the estimates of the differences between immigrants and natives in STEM with those in non-STEM sector, it appears that task specialization is more intense in the non-STEM sector. Nonetheless, the results still suggest that task specialization between immigrants and U.S. natives occurs within the STEM sector.

There are a few recent works that attempt to estimate the elasticity of substitution of similarly skilled U.S- and foreign-born without differentiating between STEM and non-STEM workers. The seminal work by Ottaviano and Peri (2012) found the elasticity estimates of around 20, although this result has been disputed by Borjas et al. (2012). The work by Manacorda et al. (2012) found the elasticity estimates between 5 to 10 in Britain. My analysis shows that the estimates range from 12 to 18 within STEM, which suggests slightly more complementarity compared to Ottaviano and Peri (2012). A potential explanation for this is that the elasticity of substitution estimates are obtained based on the sample of recent immigrants who are likely to be different from natives, similar to Manacorda et al. (2012).

1.4.2 Other Elasticity Parameter Estimates

Table 1.4 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

implies higher proficiency of a particular skill required for the occupation.

not be preferable because women's labor supply is more likely to be endogenous 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 results of the analysis show that I cannot reject that these workers are perfect substitutes in any of the specifications used (Appendix Table 1.17). 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 ($\sim$13) is relatively higher compared to Card and Lemieux (2001) and Ottaviano and Peri (2012), who did not differentiate between the STEM and non-STEM workers ($\sim$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 1.5 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. This could be caused by the tasks performed across education groups within STEM are more similar compared to non-STEM.

Table 1.6 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 1.7 provides estimates for σ_H. The literature provides some guidance on the value of σ_H.[21] In their influential study, Katz and Murphy (1992) found the estimate of σ_H to be 1.4. Ottaviano and Peri (2012) and Peri et al. (2015) 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.[22]

1.5 Wage Effect

Now, I can use the elasticity parameter estimates obtained in the previous section to calculate the wage effect of 2000-2015 foreign STEM supply shock on the preexisting workforce. In estimating the wage 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 1.1). 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

[21] It should be noted that the division of high- and low-skilled labor to estimate σ_H in this study departs slightly from the literature. I define high-skilled labor as STEM workers of all educational attainment and non-STEM college-educated workers, while the literature usually defines high-skilled labor as workers with a college education.

[22] It is worth noting that the estimates for σ_{sc} and σ_H are based on a small number of observations (16 obs.). Although it is a cause for concern, these estimates are comparable to those usually found in the literature, as noted in the main text.

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 1.4 and 1.5 show the results of the wage effects across education-age groups in STEM sector.[23] 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. Table 1.8 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 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 1.5). 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

[23] "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 1.4 and 1.5 are the same for both U.S. and foreign-born STEM workers.

in more competition among immigrants in that particular skill group. On average, the wage of earlier STEM immigrants declines by -0.07% (Table 1.8). 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 1.9). 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%).

Comparing the wage effects estimates when similarly skilled U.S.- and foreign-born STEM workers are assumed to be perfect substitutes with the main estimates yields a few interesting findings. First, imperfect substitutability between similarly skilled U.S.- and foreign-born STEM workers does not have a substantial impact on the wage effect estimates for workers with less than a Bachelor's degree (5.84% vs. 5.76%), while it has a considerable influence on the wage effect estimates for workers with post-graduate degree (3.14% vs. 1.72%). This result mainly reflects that recent STEM immigration in the United States mostly increased the supply of STEM workers with high educational attainment. Additionally, imperfect substitutability between similarly skilled and U.S.- and foreign-born STEM workers transfers most of the wage gains that accrue to foreign-born STEM workers to U.S.-born STEM workers (-0.07% vs. 3.85%).

It may also be interesting to see how much the results change when different values of σ_{sn} and σ_{sa} are used. Since most of σ_{sn} and σ_{sa} estimates lie between 12-18 and 13-40 respectively, I check how the wage effects change when these values are used. The results are reported in Appendix Table 1.18. On average, the wage effects of 2000-2015 foreign STEM supply shocks on U.S.-born STEM workers are between 4.67% and 5.02%, while for foreign-born STEM workers, the wage effects range from -0.07% to -1.71%. If productivity spillovers are not taken into account, the impact of the supply shock on U.S.-born STEM workers is between 0.58% and 0.93% on average, while for immigrant STEM workers it is between -4.16% and -5.80%.

For low skilled workers, the wage effect is approximately 1.41% (Table 1.10). 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 1.11.

The results suggest that 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 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.

1.6 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. Finally, 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.

1.7 Figures and Tables

Table 1.1: 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 2001-2015. 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 1.2: 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)	
	[13.40]	[13.98]	
Hours as Supply	-0.070	-0.066	336
	(0.033)	(0.035)	
	[14.21]	[15.14]	
Pooled (Men and Women)	-0.070	-0.068	336
	(0.027)	(0.029)	
	[14.32]	[14.67]	
Four Education Groups	-0.056	-0.080	448
	(0.029)	(0.026)	
	[17.94]	[12.58]	
Five Education Groups	-0.066	-0.086	560
	(0.027)	(0.024)	
	[15.21]	[11.67]	

Source: IPUMS 5% 2000 Census and ACS 2001-2015. Heteroskedastic- and cluster-robust standard errors at education-age groups in parentheses; Implied elasticity of substitution reported in square 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 1.3: 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 1.4: Inverse of Elasticity of Substitution Between Age Groups within STEM ($1/\sigma_{sa}$)

	STEM		
	Census	Skill-Based	Observations
Baseline	-0.075	-0.076	336
	(0.046)	(0.043)	
	[13.40]	[13.12]	
Efficiency Units	-0.075	-0.077	336
	(0.046)	(0.043)	
	[13.30]	[12.94]	
Hours as Supply	-0.058	-0.049	336
	(0.041)	(0.039)	
	[17.19]	[20.35]	
Pooled (Men and Women)	-0.041	-0.059	336
	(0.029)	(0.030)	
	[24.14]	[17.09]	
Four Education Groups	-0.037	-0.017	448
	(0.032)	(0.032)	
	[27.39]	[60.22]	
Five Education Groups	-0.027	0.001	560
	(0.032)	(0.033)	
	[37.48]	[∞]	

Source: IPUMS 5% 2000 Census and ACS 2001-2015. Heteroskedastic- and cluster-robust standard errors at education-age groups in parentheses; Implied elasticity of substitution reported in square 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 1.5: Inverse of Elasticity of Substitution Between Education Groups within STEM ($1/\sigma_{se}$)

	STEM		
	Census	Skill-Based	Observations
Baseline	-0.147	-0.179	48
	(0.072)	(0.047)	
	[6.82]	[5.60]	
Efficiency Units	-0.147	-0.166	48
	(0.069)	(0.042)	
	[6.80]	[6.03]	
Hours as Supply	-0.123	-0.162	48
	(0.064)	(0.041)	
	[8.15]	[6.18]	
Pooled (Men and Women)	-0.080	-0.128	48
	(0.085)	(0.083)	
	[12.47]	[7.79]	
Four Education Groups	-0.071	-0.127	64
	(0.107)	(0.062)	
	[14.03]	[7.86]	
Five Education Groups	-0.055	-0.092	80
	(0.081)	(0.071)	
	[18.23]	[10.89]	

Source: IPUMS 5% 2000 Census and ACS 2001-2015. Heteroskedastic- and cluster-robust standard errors at education groups in parentheses; Implied elasticity of substitution reported in square 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 1.6: Inverse of Elasticity of Substitution Between STEM and College Non-STEM Workers ($1/\sigma_{sc}$)

	Census	Skills Based	Observations
Baseline	0.077 (0.082) [∞]	0.050 (0.060) [∞]	16
Efficiency Units	0.109 (0.114) [∞]	0.063 (0.074) [∞]	16
Hours as Supply	0.102 (0.082) [∞]	0.073 (0.056) [∞]	16
Pooled (Men & Women)	0.030 (0.085) [∞]	0.014 (0.052) [∞]	16
Pooled (Hours as Supply)	0.038 (0.094) [∞]	0.023 (0.052) [∞]	16

Source: IPUMS 5% 2000 Census and ACS 2001-2015. Newey-West heteroskedastic- and autocorrelation-consistent standard errors in parentheses; Implied elasticity of substitution reported in square 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 1.7: 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)	
	[1.38]	[1.36]	
Efficiency Units	-0.724	-0.728	16
	(0.237)	(0.237)	
	[1.38]	[1.37]	
Hours as Supply	-0.459	-0.457	16
	(0.098)	(0.096)	
	[2.18]	[2.19]	
Pooled (Men & Women)	-0.680	-0.685	16
	(0.235)	(0.237)	
	[1.47]	[1.46]	
Pooled (Hours as Supply)	-0.381	-0.378	16
	(0.062)	(0.060)	
	[2.63]	[2.64]	

Source: IPUMS 5% 2000 Census and ACS 2001-2015. Newey-West heteroskedastic- and autocorrelation-consistent standard errors in parentheses; Implied elasticity of substitution reported in square 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 1.8: 2000-2015 Foreign STEM Supply Shocks and STEM Workers' Wages

	U.S.-born		Foreign-born	
	Without Externalities	*With Externalities*	*Without Externalities*	*With Externalities*
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%**

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 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. '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 1.9: 2000-2015 Foreign STEM Supply Shocks and STEM Workers Wages - Assuming $\sigma_{sn} = \infty$

	All STEM Workers	
	Without Externalities	*With Externalities*
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%**

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 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. '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 1.10: 2000-2015 Foreign STEM Supply Shock and College Non-STEM/Low-skilled Wages

	Without Externalities	*With Externalities*
Low-skilled	0.60%	1.41%
College Non-STEM	-0.24%	3.85%

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 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. '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 1.11: 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).

Figure 1.1: STEM Sector Characteristics Over Time

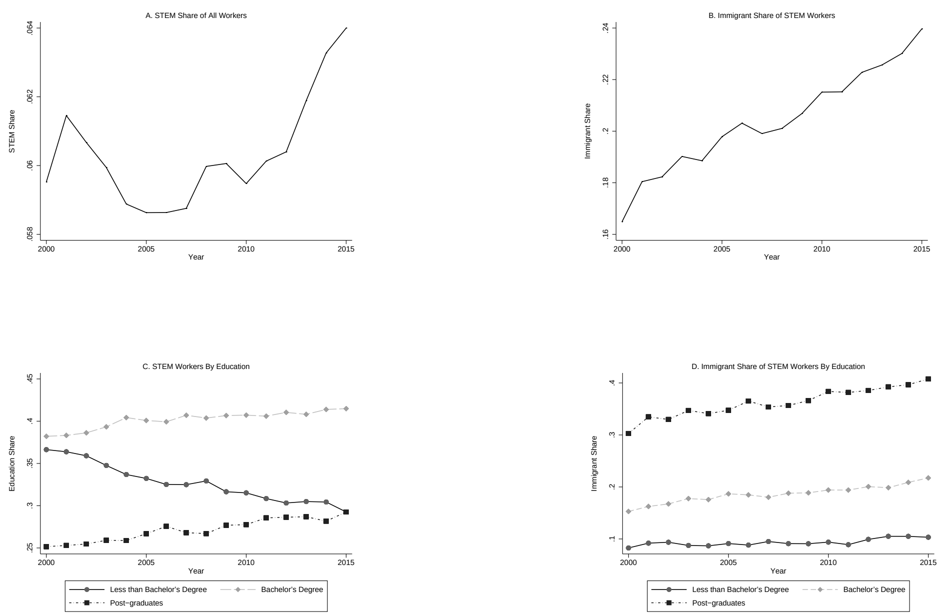


Figure 1.2: Old and Young Wages in STEM

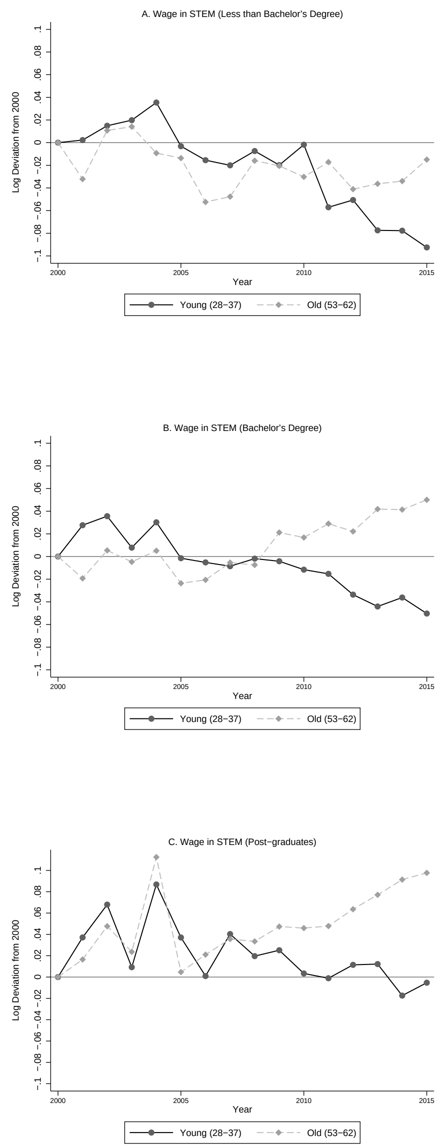
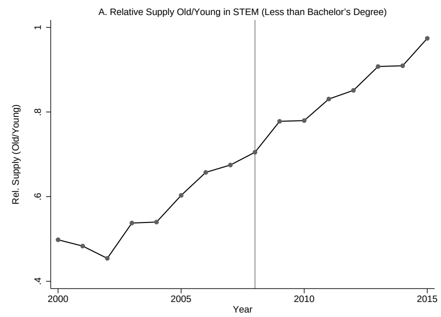
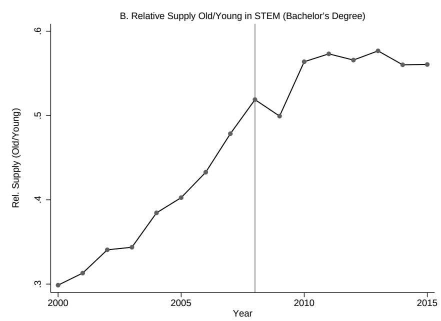


Figure 1.3: Relative Supply Old/Young in STEM





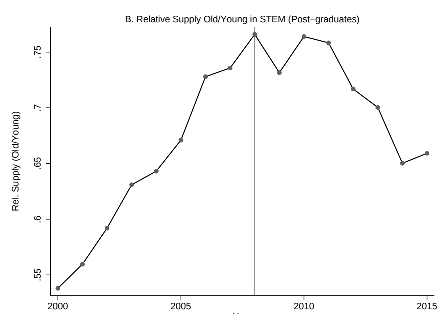


Figure 1.4: 2000-2015 Foreign STEM Supply Shock and Native STEM Workers' Wages With Spillover Effect

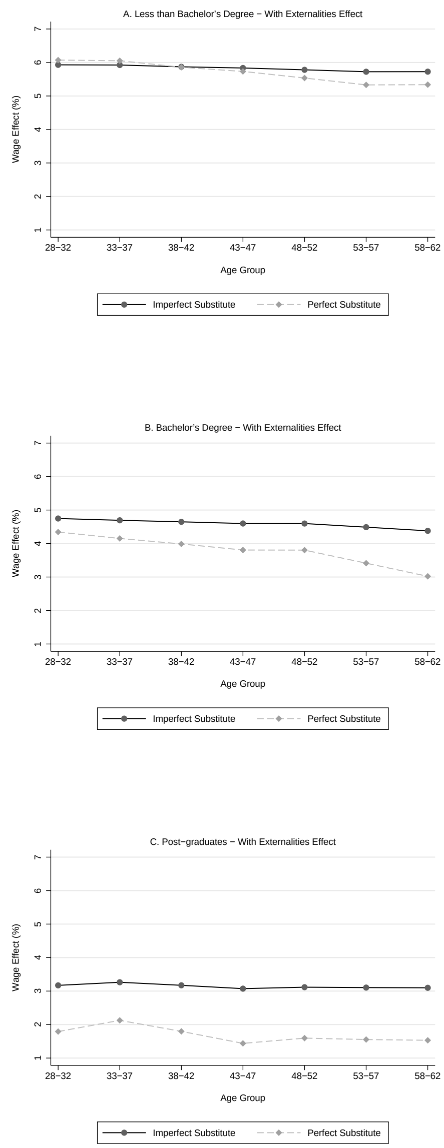
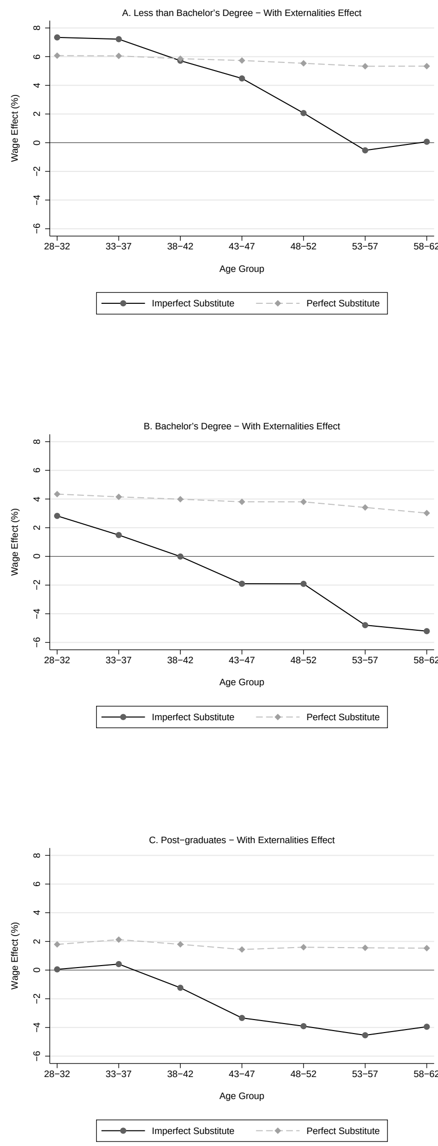


Figure 1.5: 2000-2015 Foreign STEM Supply Shock and Immigrant STEM Workers' Wages with Spillover Effects



1.8 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.

1.9 Appendix B

Table 1.12: 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	

Table 1.13: Additional Robustness Checks Stricter Census STEM Classification (Excluding STEM Technician Occupations)

	$1/\sigma_{sn}$	$1/\sigma_{sa}$	$1/\sigma_{se}$
Baseline	-0.087	-0.062	-0.202
	(0.037)	(0.049)	(0.074)
	[11.52]	[16.08]	[4.96]
Hours as Supply	-0.076	-0.037	-0.164
	(0.036)	(0.041)	(0.065)
	[13.20]	[26.98]	[6.09]
Pooled (Men and Women)	-0.076	-0.024	-0.114
	(0.029)	(0.034)	(0.074)
	[13.10]	[41.79]	[8.78]
Four Education Groups	-0.059	-0.039	-0.126
	(0.033)	(0.040)	(0.081)
	[16.83]	[25.43]	[7.95]
Five Education Groups	-0.083	-0.009	-0.101
	(0.032)	(0.034)	(0.064)
	[12.07]	[108.65]	[9.88]

Source: IPUMS 5% 2000 Census and ACS 2001-2015. Heteroskedastic- and cluster-robust standard errors at education groups in parentheses; Implied elasticity of substitution reported in square brackets. All regressions are weighted by the inverse of the sampling variance of the dependent variable.

Table 1.14: Inverse of Elasticity of Substitution Between U.S. and Foreign STEM Workers Within Skill Group ($1/\sigma_{sn}$) - Youngest Age Group Only

	STEM		
	Census	Skill-Based	Observations
28-32 Years Age Group Only	-0.156 (0.042) [6.42]	-0.154 (0.029) [6.50]	48

Source: IPUMS 5% 2000 Census and ACS 2001-2015. Heteroskedastic- and cluster-robust standard errors at education groups in parentheses; Implied elasticity of substitution reported in square 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 1.15: Share of Immigrants Across STEM Occupations

Share of Immigrants in STEM Occupations	***0.161***
Share of Immigrants in:	
Engineering	0.157
Biological, Agricultural, and Environmental Sciences	0.190
Psychology	0.108
Physical Sciences	0.256
Computer Sciences	0.175
Computer, Engineering, and Natural Sciences Manager	0.118
Other STEM occupations	0.106
Share of Immigrants within Engineering:	
Aerospace Engineers	0.149
Chemical Engineers	0.159
Civil Engineers	0.167
Computer Hardware Engineers	0.266
Electrical and Electronics Engineers	0.186
Environmental Engineers	0.122
Industrial Engineers, including Health and Safety	0.110
Marine Engineers and Naval Architects	0.104
Materials Engineers	0.143
Mechanical Engineers	0.152
Petroleum, mining and geological engineers, including mining safety engineers	0.112
Engineers, nec	0.192
Engineering Technicians, Except Drafters	0.124
Sales Engineers	0.086

Notes: The estimates are obtained from IPUMS 5% 2000 Census.

Table 1.16: Occupation Skills Descriptive Statistics

	Mathematics Skill				*Speaking Skill*			
	Immigrants	*Natives*	*Immigrants-Natives*	*Diff. p-value*	*Immigrants*	*Natives*	*Immigrants-Natives*	*Diff. p-value*
Panel A: STEM								
All	3.570	3.498	0.072	0.000	3.797	3.813	-0.016	0.000
Young (28-37 Yrs. Old)	3.550	3.489	0.061	0.000	3.785	3.811	-0.026	0.000
Old (53-62 Yrs. Old)	3.657	3.537	0.120	0.000	3.818	3.825	-0.007	0.016
Panel B: Non-STEM								
All	2.249	2.511	-0.262	0.000	3.130	3.410	-0.280	0.000
Young (28-37 Yrs. Old)	2.250	2.480	-0.231	0.000	3.108	3.391	-0.283	0.000
Old (53-62 Yrs. Old)	2.248	2.522	-0.274	0.000	3.151	3.416	-0.265	0.000

Notes: Estimates based on ACS 2010-2015 and U.S. Department of Labor O*Net data. The analysis used both men and women of age 28 to 62. STEM occupations are defined using Census 2010 STEM classification.

Table 1.17: Estimates of $(1/\sigma_{se})$ for Lower Education Group in STEM

	STEM		
	Census	Skill-Based	Observations
Baseline	0.074 (0.050) [∞]	0.041 (0.059) [∞]	48
Hours as Supply	0.067 (0.056) [∞]	0.023 (0.073) [∞]	48
Pooled (Men and Women)	0.041 (0.059) [∞]	-0.019 (0.054) [52.36]	48
Pooled (Hours as Supply)	0.050 (0.053) [∞]	-0.019 (0.054) [53.46]	48

Source: IPUMS 5% 2000 Census and ACS 2001-2015. Heteroskedastic- and cluster-robust standard errors at education groups in parentheses; Implied elasticity of substitution reported in square 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 1.18: Immigrant STEM Supply Shock and STEM Workers Wage (2000 - 2015) - Different Values of σ_{sa} and σ_{sn}

	U.S.-born		Foreign-born	
	Without Externalities	*With Externalities*	*Without Externalities*	*With Externalities*
Panel A: (σ_{sa}=13 and σ_{sn}=12)				
Less than Bachelor's Degree	1.79%	5.89%	0.21%	4.30%
Bachelor's Degree	0.89%	4.98%	-5.89%	-1.80%
Post-graduates	-0.22%	3.87%	-7.32%	-3.23%
STEM Average	**0.92%**	**5.01%**	**-5.77%**	**-1.67%**
Panel B: (σ_{sa}=13 and σ_{sn}=18)				
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 C: (σ_{sa}=40 and σ_{sn}=12)				
Less than Bachelor's Degree	1.80%	5.89%	0.19%	4.28%
Bachelor's Degree	0.90%	4.99%	-5.93%	-1.84%
Post-graduates	-0.21%	3.88%	-7.36%	-3.26%
STEM Average	**0.93%**	**5.02%**	**-5.80%**	**-1.71%**
Panel C: (σ_{sa}=40 and σ_{sn}=18)				
Less than Bachelor's Degree	1.75%	5.84%	0.68%	4.78%
Bachelor's Degree	0.55%	4.64%	-3.99%	0.10%
Post-graduates	-0.93%	3.16%	-5.69%	-1.60%
STEM Average	**0.59%**	**4.68%**	**-4.20%**	**-0.11%**

The wage effect is estimated using $\sigma_H = 2$, $\sigma_{sc} = \infty$, $\sigma_{se} = 6$, and actual wage shares in 2000 with pooled (men and women) sample. The wage effect 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. '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).

Chapter 2

On the Association Between Undocumented Immigration and Crime in the United States

Crimes are costly for society. Cohen (1988) estimated that the annual cost of crime to the victims is approximately 92.6 billion USD in the United States. Similarly, Miller et al. (1993) estimated that violent crime led to 23 billion USD in lost productivity and approximately 145 billion USD in reduced quality of life in the United States. At the same time, there are concerns that an increase in immigration may lead to a sizable increase in crime rates. When asked about the consequence of more immigrants coming into the United States, almost half of the respondents of Gallup polling in 2017 stated that immigrants make the crime situation worse. Therefore, immigration - especially undocumented immigration - may impose a cost to society through an increase in crime rates. In this article, I examine the institutionalization (incarceration) rate of undocumented immigrants and quantify the change in crime rates attributable to undocumented immigration.

The empirical literature on immigration and crime in the U.S. seems to broadly agree that immigrants are no more or even less likely to participate in criminal activity compared to U.S. natives (Butcher and Piehl, 1998b,a; Reid et al., 2005; Moehling and Piehl, 2009; Stowell et al., 2009). However, there are reasons to believe that undocumented immigrants would be more likely to commit crime compared to those who are legally in the United States or U.S. natives.[1] Undocumented immigrants are overrepresented among low-skilled workers (Figure 2.1), which makes the returns from participating in informal labor markets - such as crime - relatively higher for them. Furthermore, undocumented immigrants are more likely to be younger men (Figure 2.2 and 2.3), which is the group that is more frequently involved in criminal activity than others (Freeman, 1999). Therefore, an increase in the share of undocumented immigrants in the population may lead to a higher crime rate.

On the other hand, undocumented immigrants may have the most incentive to not commit a crime because contact with law enforcement even for a minor offense would increase the probability that their illegal status would be revealed. For example, Butcher and Piehl (2007) argue that one of the reasons of why immigrants who arrived most recently are less likely to commit a crime is the higher share of undocumented immigrants in the recent immigrant cohorts. It is possible, therefore, that an increase in the share of undocumented immigrants in the population would lead to lower crime rates.

I proceed as follows in analyzing the connection between undocumented immigration and crime. First, I examine the institutionalization rate of undocumented immigrants compared to other U.S. residents. A higher institutionalization rate would give an indication that undocumented immigrants are indeed more likely to commit a crime once they are in the United States compared to other U.S. residents. Then, I examine whether undocumented immigration contributes to a sizable increase in crime rates. Although undocumented immigrants might be more (less) likely to commit a crime compared to those who are legally in the U.S. or natives, undocumented immigration may not necessarily

[1] It should be noted that illegal/improper entry into the United States carries criminal penalties and thus constitutes a crime. The subject of this article is therefore whether undocumented immigrants are more likely commit a crime once they are in the U.S. (i.e., other than the one that they already did by illegally crossing the border) and whether their presence contributes to the increase in crime rates.

increase (lower) crime rates. Previous studies have noted that immigration may increase labor market competition among other U.S. residents, worsening their labor market outcomes and incentivizing them to commit a crime (Borjas et al., 2010). At the same time, undocumented immigration may spur job creation and improve labor market outcomes of U.S. natives and legal residents (Chassamboulli and Peri, 2015), which in turn lowers crimes (Gould et al., 2002). Therefore, the question of whether undocumented immigration has an adverse effect on crime rates depends not only on the likelihood of undocumented immigrants committing a crime but also on the resulting externalities that may increase or reduce crime rates.

At the individual level, I find that undocumented immigrants are approximately 33% less likely to be institutionalized compared to U.S. natives. After accounting for differences in background characteristics such as education and age, the institutionalization rate gap between U.S-born individuals and undocumented immigrants becomes even larger. I also find no evidence that undocumented immigrants who have spent more time in the U.S. are more likely to be institutionalized compared to those who have been in the U.S. for a shorter time. However, there is evidence that arriving at a younger age is associated with higher institutionalization rate.

The analysis of whether undocumented immigration increases crime rates across U.S. states is complicated by a few factors that may bias the effect of interest. For example, undocumented immigrants may endogenously select where they migrate to. Then, in response to the inflow of undocumented immigrants, the other U.S. residents may choose to leave or migrate into the area. Furthermore, there may be a systematical underreporting of crime in the state where there is a large share of undocumented immigrants because they are less likely to report a crime because of fear of deportation.[2] To address these concerns, I use two instrumental variable approaches. First, following Altonji and Card (1991) and Card (2001), I use the historical regional patterns of settlement of undocumented immi-

[2] Indeed, a study by Comino et al. (2016) suggests that undocumented immigrants are almost four times less likely to report crimes compared to U.S. natives.

grants from a source country to predict the subsequent flow of undocumented immigrants from the source country into a state. This approach, although widely used in immigration literature, has been argued to not satisfy exclusion restriction condition for a valid instrument because factors that pull migrants into a particular destination in the past may be correlated with the crime rate in the destination today (Chalfin, 2013). Therefore, in the spirit of Angrist and Kugler (2003) and Llull (2017) who used push factors (e.g., wars or economic conditions in the source country) to identify the wage effect of immigration, I create a similar instrument based on active conflict events in Mexico that become prevalent after 2000. The results from both approaches show that the overall property and violent crime rates across U.S. states are not significantly increased by undocumented immigration.

This paper contributes to the literature that examines whether immigrants are more likely to commit a crime compared to U.S. natives. So far, this literature has focused on the average immigrant, without differentiating their legal status (e.g., Butcher and Piehl, 1998b; Moehling and Piehl, 2009). However, it is unlikely that undocumented immigrants are equally likely as legal immigrants to participate in crime considering that their unauthorized status would limit their opportunities in the job market. Indeed, a few recent studies have documented that granting legal status to unauthorized immigrants lowers their probability of committing a crime in Europe (Mastrobuoni and Pinotti, 2015; Pinotti, 2017). A closely related study to this paper is the CATO Institute Research and Policy Brief by Landgrave and Nowrasteh (2017), which also examines the difference in institutionalization rate between undocumented immigrants and other U.S. residents. However, their illegal status imputation method that does not exclude some high-skilled foreign-born individuals employed in licensed occupations from undocumented immigrant pool might lead to an overestimation in the gap of institutionalization rate between undocumented immigrants and natives.[3] Furthermore, their analysis did not test whether this gap is statistically significant nor try to take into account the difference in background characteristics between

[3]Landgrave and Nowrasteh (2017) found that undocumented immigrants are 44% less likely to be institutionalized than U.S. natives.

undocumented immigrants and other U.S. residents in their analysis. This paper extends the work of Landgrave and Nowrasteh (2017) by improving on the methodology and by examining whether assimilation, age at arrival, and arrival cohort play a role in determining the institutionalization rate of undocumented immigrants.

This paper also contributes to the literature that examines the nexus of immigration and crime at an aggregate level. The literature has mainly focused on the overall immigration thus far (e.g., Butcher and Piehl, 1998a; Bianchi et al., 2012; Bell et al., 2013). However, the interest of recent policy debates has been mainly on undocumented immigration, which is the focus of this paper. Recently, a few studies have documented that legalization policies lead to a reduction in the crime rates (Baker, 2015; Fasani, 2018). It is natural to generalize the finding of these studies as implying that an increase in the share of undocumented immigrants in the population would increase crime rates. However, it is worth noting that the effect of an increase in the share of undocumented immigrants in the population on crime rates may not necessarily be symmetric as the effect of lowering it through legalization policy. For example, following the passage of legalization policy in the U.S. (IRCA), applicants who were convicted of a felony or three misdemeanors during the 18-months probationary period would be removed from the programs, exerting incentive to not commit crime among the would be legal immigrant during this period. It is plausible that this effect would be long-lasting if the applicants believe that their status could be revoked long after the probationary period. Therefore, although a decrease in the share of the undocumented population caused by legalization policies reduces crime rates, a rise in the share of the unauthorized population may not necessarily increase it.[4] It is also possible that undocumented immigrants who were legalized due to IRCA have different propensity to commit crimes compared to those who arrived after IRCA, suggesting the need to examine how crime rates respond to the movement of undocumented immigrants in other settings.

[4]In a different context to this study, recent works by Clemens et al. (2018) and Lee et al. (2017) have also argued that the wage and employment effects of an increase in the population of migrants are not symmetric as reducing it through immigration restriction policy.

Another closely related study to this paper is Light and Miller (2018), who also examines the effect of undocumented immigration on violent crimes in the U.S. context. Conducted independently and at the same time as this paper, the authors found no evidence that undocumented immigration increases violent crime rates across the U.S. states. This paper complements the finding of Light and Miller (2018) in two ways. First, I analyse the association between undocumented immigration and crime using an instrument that does not rely on the past settlement of immigrants, which has been shown to be unlikely to meet the exclusion restriction requirement for a valid IV (Jaeger et al., 2018). Second, I examine whether undocumented immigration is associated with an increase in property crime rates across the U.S. states. I believe investigating this is important, especially because undocumented immigrants have fewer employment opportunities compared to legal immigrants caused by their illegal status, making them more vulnerable to committing crimes for financial gains rather than "crimes of passion" (violent crimes). [5]

The remainder of the paper is organized as follows. Section 2 describes the procedure used to impute undocumented status in census data. Section 3 examines the institutionalization rate of undocumented immigrants compared to other U.S. residents. Section 4 analyses the impact of undocumented immigration on crime rates in the United States. Section 5 concludes.

2.1 Imputing Undocumented Status in Census Data

The U.S. Census Bureau does not ask the immigration status of the respondent. However, it is possible to impute the legal status of immigrants based on the characteristics of the respondent. For example, since a large share of undocumented immigrants come from Mexico and Central America, Orrenius and Zavodny (2016) defined those who are unauthorized as "immigrants aged 20-54 who have at most completed high school, are from

[5] For example, Bell et al. (2013) found that the wave of asylum seekers in the UK increase the property crime rates. The authors attributed this result to the limited labor market opportunities among the asylum seekers.

Mexico and Central America, and are not US citizens." Similarly, Passel and Cohn (2014) from Pew Research Center creates a methodology to impute undocumented status in American Community Survey and CPS Annual Social and Economic Supplement dataset. The ACS and CPS dataset with imputed undocumented status from Passel and Cohn (2014) are not publicly available. However, Borjas (2017b,a) was granted access to the 2012-2013 CPS ASEC files that Passel and Cohn (2014) constructed, and the author suggested that it may be possible to "reverse engineer" the method that was used to create the imputed undocumented status based on a number of characteristic variables available in the census microdata. Following Borjas (2017b,a), I classify a foreign-born person as a legal immigrant if any of the following conditions holds:

a. that person arrived before 1980;

b. that person is a citizen;

c. that person receives welfare benefits such as Social Security, SSI, Medicaid, Medicare, or military insurance;

d. that person is a veteran or is currently in the Armed Forces;

e. that person works in the government sector;

f. that person resides in public housing or receive rental subsidies, or that person is a spouse of someone who resides in public housing or receive rental subsidies[6];

g. that person was born in Cuba;

h. that person's occupation requires some form of licensing;

i. that person's spouse is a legal immigrant or citizen.

All other foreign-born persons who are not classified as legal immigrants are assumed to be undocumented. It is worth noting that this method may overestimate the population of undocumented immigrants because some of the legal immigrants are classi-

[6]Because there is no information on whether someone resides in public housing or receives rental subsidies in IPUMS 5% 2000 Census or ACS, similar to Borjas (2017a), I did not apply this condition to impute undocumented status.

fied as undocumented. For example, a person on a temporary student visa or high-skilled (H1-B) visa holder who is employed in an occupation that does not require a license would be classified as an undocumented immigrant. Assuming that a highly educated person is less likely to commit a crime, then this misclassification would cause the estimates to be biased in the direction that shows that the crime rates are negatively associated with undocumented immigration, and undocumented immigrants are less likely to be institutionalized relative to other U.S. residents. However, we can do a simple back of the envelope calculation to estimate an approximate number of how many legal immigrants are misclassified as undocumented. For example, Ruiz (2014) estimated that there are about 450,000 foreign students in the U.S. in 2008. At the same time, Kerr and Lincoln (2010) used the demographic model from Lowell (2000) and estimated that there is approximately 500,000 H-1B visa holder in the U.S. between 2002 and 2008. As there are about 12.3 million individuals classified as undocumented from the ACS in 2008, assuming that the misclassification error is similar to its level in 2008, this would lead to approximately 7.7% of legal residents classified as undocumented in the sample.[7] Although this misclassification error might be arguably small to substantially affect the estimates, it should be noted that the estimates might be biased in the direction that shows that the crime rates are negatively associated with undocumented immigration, and undocumented immigrants are less likely to be institutionalized relative to other U.S. residents. It is also possible that this method may classify some undocumented immigrants as legal migrants. For example, the share of Hispanics in the sample is approximately 50%, while according Pew Research Center estimate, more than half of undocumented immigrants is Hispanics.[8] The direction of the bias in the estimates caused by this misclassification error would likely depend on the propensity to commit crimes of undocumented Hispanics misclassified as legal migrants compared to that of the other U.S. residents.[9] Figure 2.4 shows the share of a foreign-born person classified

[7]Note that in this simple calculation, I did not take into account some H1-B visa holders who are employed in licensed occupations. Therefore, it is likely that this estimate of misclassification error is lower.

[8]http://www.pewresearch.org/fact-tank/2017/04/27/5-facts-about-illegal-immigration-in-the-u-s/

[9]Studies have found that the propensity to be involved in crimes among Hispanics falls between non-Hispanic whites and blacks, and almost all of this differential between Hispanics and non-Hispanic whites

as undocumented in the sample from 2000 to 2015. The share of undocumented persons is relatively stable at approximately 4% of the population, while the share of legal immigrants slightly increased from 7% to 9%.

2.2 Incarceration Rate of Undocumented Immigrants

2.2.1 Relative Incarceration Rate

Now, I examine the incarceration rate of undocumented immigrants compared to other U.S. residents by using the American Community Survey (ACS) data from 2006 to 2015 available from IPUMS Ruggles et al. (2015). Although the ACS data allow me to identify a respondent if he/she lives in an institution (i.e., correctional facilities, mental hospitals, and homes for the aged), it does not separately identify if an individual is in a correctional facility. To address this, I follow Butcher and Piehl (1998b) approach that limits the sample only to men of age 18 to 40. By using Census 1980, which was the last census from which we can separately identify individuals in different institutional settings, Butcher and Piehl (1998b) shows that the vast majority of institutionalized men between 18 to 40 years old are indeed in correctional facilities, and their results are not substantially affected when the institutionalization rate is used in the analysis[10].

Table 2.1 shows the descriptive statistics for the sample when it is restricted to only men aged 18 to 40. In this sample, the share of individuals classified as legal immigrants is approximately similar to those classified as undocumented, which is capturing the fact that undocumented immigrants are more likely to be younger men, while legal immigrants are

can be explained by the differences in their social and economic characteristics (Martinez Jr, 1997; Phillips, 2002).

[10]Similarly, Borjas et al. (2010) use institutionalization rate as a proxy for incarceration rate to examine the increase in incarceration rate of African-American following immigrant supply shock. There is a concern that the Census Bureau in many cases imputed the information on citizenship question for individuals who live in an institution, leading to a bias in the institutionalization rate of immigrants (Vaughan and Camarota, 2009). However, as noted by Vaughan and Camarota (2009), the Census Bureau imputed the citizenship question for individuals living in an institution only 6% of the time in ACS, suggesting the reliability of the data. It is also worth noting that this issue only applies to individuals living in a institution and the overall Census does not suffer from this problem (Vaughan and Camarota, 2009).

more likely to be female and older (Figures 2.2 and 2.3). A large share of those who are undocumented are of Hispanic origin (50%) - compared to 29% for legal immigrants and 11% for U.S. natives. Similarly to the full sample, undocumented immigrants in this restricted sample are overrepresented in high school dropouts category (42%) and underrepresented in college-educated category compared to other U.S. residents.

Figure 2.5 shows the institutionalization rate by residency status of U.S. population from 2000 to 2015. The institutionalization rate among all groups is relatively stable during this period. However, the institutionalization rate of undocumented immigrants (∼2%) are smaller compared to U.S. natives (∼3%). This result implies that undocumented immigrants are approximately 33% less likely to be institutionalized compared to U.S. natives, which might be surprising because undocumented immigrants have many characteristics that are usually associated with crime.[11] To formally test the difference of institutionalization rate between U.S. natives and immigrants, I run the following simple regression:

$$y_{ist} = \gamma_0 + \alpha_1 U_{ist} + \mu_1 D_{ist} + X_{ist}\beta + \delta_{st} + \varepsilon_{ist} \tag{2.1}$$

where y_{ist} is an indicator variable that is equal to one if individual i in state s at time t is institutionalized and zero otherwise. U_{ist} and D_{ist} indicate undocumented and documented status, respectively. x_{ist} is a vector of individual characteristics such as age and education. δ_{st} is state-year fixed effects to absorb the differences in policing/enforcement environment or other unobservables that may vary across states over time.

[11] There is a concern that undocumented immigrants might be deported prior to serving their sentences, which then leads to the underestimation of their institutionalization rate. However, the immigration statute (U.S. Code Title 8 Chapter 12 Section 1231) does not allow aliens (i.e., legal or undocumented immigrants) who are sentenced to imprisonment to be removed (deported) from the country until he/she is released from imprisonment. An exception can be made only in a case in which an alien was convicted of a non-violent offense and the appropriate official (the attorney general or the chief of the state prison system) requests early removal after considering if such action is appropriate and in the best interest of the United States. At the same time, it is possible for institutionalization rate of undocumented immigrants to be inflated because immigrants under deportation order spent more time incarcerated for a given sentence than similar natives (Butcher and Piehl, 2000). This may be caused by administrative delays or backlogs in the system that resulted in more immigrants waiting in prisons while awaiting their deportation process to be cleared.

Table 2.2 shows the results of the regression. Column (1) shows that the institutionalization rate gap that was observed in Figure 2.5 is indeed statistically significant. The rest of the columns shows that the gap in institutionalization rate between U.S. natives and undocumented immigrants widens with additional controls. After all the differences in background characteristics are controlled for, the estimates show that undocumented immigrants' institutionalization rate is slightly lower even when compared to those who are in the U.S. legally, although this difference is not statistically significant with a p-value of 0.49.

The finding that institutionalization rate of undocumented immigrants is similar to legal immigrants is interesting, especially because recent studies have documented that granting legal status to unauthorized immigrants lowers their probability of committing a crime in Europe (Mastrobuoni and Pinotti, 2015; Pinotti, 2017). A concern is that I did not control for important variables that may play a role in determining the difference in institutionalization rate between legal and undocumented immigrants, such as years since migration and country of origin. To examine this, I re-run the analysis using the sample of immigrants only and add years since migration and country of origin as additional controls. After controlling for years since migration and country of origin, the results show that undocumented immigrants are more likely to be institutionalized compared to legal immigrants, suggesting that legal status is associated with lower propensity to commit a crime among immigrants (Table 2.3).

2.2.2 Assimilation, Age at Arrival, and Cohort Effects

The number of years spent in the United States has been known to improve the earnings of immigrants as they obtain U.S. specific skills and information that natives have (Chiswick, 1978). Similarly, immigrants who arrive in the U.S. at a younger age are more likely to be successful in assimilating to U.S. labor market compared to those who arrive at an older age (Friedberg, 1992). Considering that individuals with poor labor market outcomes are more likely to commit a crime, it follows that we may expect that individuals who arrive at a younger age and have spent more time in the U.S. are less likely to be institutionalized. At the same time, it may take some time for immigrants to become accustomed to U.S. norms and involved in activities that resulted in institutionalization. It is possible, therefore, that immigrants who have been in the U.S. longer are very similar to U.S. natives in their probability to be institutionalized.

To examine if assimilation and age at arrival have an effect on the relative institutionalization rate of undocumented immigrants, I exclude legal immigrants from the sample (so that the reference group is U.S. natives) and estimate the following regression model in each of ACS cross sections:

$$y_{i\tau} = \gamma_{0,\tau} + \gamma_{1,\tau} X_{i\tau} + \gamma_{2,\tau} A_{i\tau} + \sum_h \gamma_{h,\tau} C_{h,i\tau} + \varepsilon_{i\tau} \tag{2.2}$$

where $y_{i\tau}$ is equal to one if individual i in cross section τ is institutionalized and zero otherwise. I consider 2007, 2011, and 2015 ACS cross sections in the analysis. A represents age at arrival, and C_h is an indicator variable if an undocumented immigrant belongs to arrival cohort h (i.e., C_{90} is an indicator if year of immigration is on or before 1990, C_{91-94} is an indicator if year of immigration is from 1991 to 1994, C_{95-98} is an indicator if year of immigration is from 1995 to 1998, and so on). For U.S. natives (the reference group), the age at arrival A and arrival cohort C_h are set to be equal to zero.[12] X is a set of control variables that includes education and current age. ε is the error term.

To examine whether undocumented immigrants are becoming more likely to be institutionalized as they spend more time in the United States (i.e., assimilation effect), we can take a look at the changes in the relative institutionalization rate of undocumented immigrants who belong to the same cohort between 2007 and 2015. In terms of the regression above, this can be computed as $\gamma_{h,2015}$ - $\gamma_{h,2007}$. Furthermore, to see if there are changes in relative institutionalization rate across cohorts (e.g., recent cohorts might be more likely to

[12] There are some cases in which age at arrival has a value of -1 or 0, which may imply that the individual had not had his/her first birthday when immigrating into the United States. For these individuals, I assign a value of one for their age at arrival.

be institutionalized compared to U.S. natives compared to earlier cohorts), we can compare the relative institutionalization rate of a cohort at a given number of years since immigration to the relative institutionalization rate of earlier cohorts at that same number of years since migration. For example, we can compare 2011-2014 cohort in 2015 with 2003-2006 cohort in 2007 because they have been in the U.S. for a similar number of years (1 to 4 years). In terms of the coefficients above, this cohort effect can be computed as $\gamma_{11-14,2015}$ - $\gamma_{03-06,2007}$.

Table 2.4 shows the effect of assimilation and age at arrival effects on relative institutionalization rate of undocumented immigrants. The estimates suggest that undocumented immigrants who arrived a year younger are 0.1 percentage points more likely to be institutionalized. For illustrative purpose, consider the institutionalization rate among undocumented immigrants who arrive when they are nine years old. Since 3.2% of undocumented immigrants who arrive when they are nine years old are institutionalized in the sample, the finding suggests that if this group arrives in the U.S. a year older, holding all else constant, their institutionalization rate would be lower by approximately 3%. The assimilation effects are negative but statistically insignificant, suggesting that the institutionalization rate of undocumented immigrants is not converging to that of U.S. natives as they spend more time in the United States. It should be noted that these estimates may underestimate the assimilation effect because deportation may remove undocumented immigrants who are more likely to be institutionalized over time. For example, undocumented immigrants from 2003-2006 cohort who are institutionalized in 2007 might be removed from the country by 2015, and because those who are deported are more likely to commit a crime, the relative institutionalization rate decreased for that cohort in 2015. To see if deportation could explain the results, I follow Butcher and Piehl (2007) approach that examines the assimilation effect for naturalized citizens. Considering that naturalized citizens are not subject to deportation after committing a crime, a widening gap in the institutionalization rate between U.S. natives and naturalized citizens over time would provide suggestive evidence that the findings in Table 2.4 are not driven by deportation. Similar to Butcher and Piehl (2007), the results show a decline in relative institutionalization rate among naturalized citizens even for different cohorts and time periods that are considered in this study (Table 2.5), suggesting that deportation is unlikely to play a major role in explaining the assimilation effect estimates observed among undocumented immigrants in Table 2.4.

Borjas (1985) noted that the qualities of immigrants across cohorts are different - with earlier cohorts being more likely to be more successful in the U.S. labor market compared to recent cohorts. Since an individual's labor market performance is correlated with his/her likelihood to commit a crime, we may expect to see a higher relative institutionalization rate among undocumented immigrants in the recent cohorts. Table 2.6 shows no robust evidence that recent cohorts are more likely to be institutionalized compared to older cohorts. The results show that undocumented immigrants in 2011-2014 cohort are more likely to be institutionalized by 2.8 percentage points compared to the 2003-2006 cohort, but it is not statistically significant at the conventional levels. Qualitatively similar results are observed for other cohort comparisons.

The analysis so far examines the assimilation effect of undocumented immigrants using natives as the reference group. However, it is also possible to examine how the institutionalization rate of undocumented immigrant changes over time relative to that of legal immigrants. The result of this exercise is reported in Table 2.7. The evidence suggests that the institutionalization rate of the 2003-2006 cohort is converging toward that of legal immigrants. However, this is not the case for the earlier cohorts. Therefore, there is no robust evidence that the institutionalization rate of undocumented immigrants is converging toward that of legal migrants.

2.3 Undocumented Immigration and Crime Rates

The results from the previous section show that undocumented immigrants are less likely to be institutionalized and thus provide a suggestive evidence that they are less likely to commit a crime compared to U.S. natives. In this section, I examine whether an inflow of undocumented immigrants increases crime rates. As noted before, the impact of undocumented immigration on crime rates is ambiguous even though undocumented immigrants might be less likely to commit a crime at an individual level compared to U.S. natives. For example, worsening labor market conditions have been shown to increase crime rates in the U.S. (Gould et al., 2002). At the same time, immigration has been thought to worsen the labor market outcomes of natives (e.g., Borjas, 2003; Borjas et al., 2010), although many studies argue that the labor market effect of immigration is relatively small (Card, 1990, 2005; Ottaviano and Peri, 2012). Recently, undocumented immigration has been suggested to spur job creation because the expected value of posting a vacancy is higher in a place where there is a larger share of undocumented immigrants (Chassamboulli and Peri, 2015). Therefore, the impact of undocumented immigration on crime rates depends not only on the likelihood to commit a crime among undocumented immigrants, but also on the resulted externalities that may induce or reduce crimes committed by other U.S. residents.

To examine the impact of undocumented immigration on crime rates, I consider the following regression:

$$y_{st} = \gamma_1 + \beta_1 u_{st} + \delta_s + \delta_t + \delta_s t + e_{st} \tag{2.3}$$

where y_{st} is the crimes per 100,000 population in state s at time t. The violent and property crimes data are obtained from the FBI Uniform Crime Report. u_{st} is the share of undocumented immigrants in the population in state s at time t. It is obtained by aggregating undocumented individuals at the state level and then dividing it with total population in the state. δ_s and δ_t are state and year fixed effects, while $\delta_s t$ is the state time trend to control for state-specific factors that vary (linearly) over time. For this analysis, I use IPUMS 5% 2000 Census and ACS data from 2001 to 2015, yielding 816 annual observations from 2000 to 2015. I conduct the analysis at the state level to minimize bias caused by measurement error and the response of other U.S. residents to the inflow of undocumented immigrants.[13]

[13]For example, it may be harder for U.S. natives to move to other states than to move to another city within a state following an inflow undocumented immigrants. Borjas (2006) and Aydemir and Borjas (2011)

The coefficient of interest is β_1, which measures the change in crime rates associated with a one percentage point increase in the share of undocumented immigrants.[14]

As previously noted, estimating equation (3) by a simple OLS regression may lead to biased estimate caused by the endogenous location of undocumented immigrants and systematic underreporting in a state where there is a higher share of undocumented immigrants. To minimize the bias, I follow Altonji and Card (1991) and Card (2001), who use the historical regional patterns of settlement of undocumented immigrants from a source country to predict the subsequent flow of undocumented immigrants from the source country into a state - which is usually known as "network instrument." This instrument relies on the tendency of new immigrants to settle in an area with a large share of immigrants from the same country (Bartel, 1989), possibly because of lower information costs associated with ethnic networks. Formally, the predicted share of undocumented immigrants is written as

$$\widehat{u_{st}} = \frac{\sum_{c=1}^{9} U_{ct} \times \frac{U_{cs,1990}}{U_{c,1990}}}{Population_{st}} \tag{2.4}$$

where U_{ct} is the total number of undocumented immigrants from country of origin c at time t.[15] $\frac{U_{cs,1990}}{U_{c,1990}}$ represents the share of undocumented immigrants from country c who were living in state s in 1990.

Although widely used in the literature, network instrument has been argued to not satisfy exclusion restriction conditions for a valid instrument because factors that pull migrants into a particular destination in the past may be correlated with the crime rate in the destination today (Chalfin, 2013). Recently, the work by Jaeger et al. (2018) has argued that an instrument that relies on past settlement of immigrants is unlikely to be a valid IV in the context of wage effect of immigration because it conflates the short-term effect with

outline these problems of measurement error and native internal migration in the context of wage effect of immigration.

[14] For ease of interpretation, the regression coefficient β_1 has been divided by 100, so that it shows the effect of one percentage point increase in the share of undocumented immigrants on crime rates.

[15] Following Spenkuch (2013), I aggregate countries into nine groups: Northwestern Europe, Eastern Europe, Southern Europe, Asia, Mexico, South and Central America, Africa, Canada, and all other countries.

the long-run adjustment effects (e.g., capital adjustment). In my case, if undocumented immigration leads to an adjustment that reduces crimes in the long-run, then the estimates obtained from using network instrument would be biased downward. In the light of these studies, there is a need to construct an instrument that does not rely on past settlement of immigrants.Therefore, in the spirit of Angrist and Kugler (2003) and Llull (2017) who used push factors (e.g., wars or economic conditions in the source country) to identify the wage effect of immigration, I create a similar instrument based on active conflict events in Mexico that become prevalent after 2000.[16] Figures 2.6 shows the casualties from active conflict events in Mexico in three time periods: 1990 to 1999, 2000 to 2009, and 2010 to 2015. Between 1990 and 1999, there were only two active conflicts events in the Mexican state of Chiapas, which took place as a protest to the NAFTA agreement in 1994, but continued in 1997 after peace talks stagnated. The conflicts spread to more Mexican states and became more intense after the Mexican government took a stronger stance against drug cartels beginning in the 2000s. The justification for the push instrument comes from the fact that the majority of undocumented immigrants come from Mexico (Rosenblum and Ruiz Soto, 2015), so that factors that push people to migrate away from Mexico (e.g., wars or conflicts) are expected to increase the share of undocumented immigrants in U.S. states that are close to the place of conflict.[17] Formally, I formulate the push instrument as an index that assigns a higher value to the state that is predicted to receive a larger inflow of undocumented immigrants following conflicts in Mexico:

$$p_t^s = \sum_{m=1}^{32} \frac{conflict_{t-10,t}^m}{Max.conflict_{t-10,t}} \times \frac{Min.Dist.}{Dist_{sm}} \tag{2.5}$$

[16]The data for active conflict events come from UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002). I define an active conflict event as an incident of lethal violence occurring at a given time and place that resulted in at least 25 deaths.

[17]Distance has been known as a factor that mitigates the migration of people from their home country into the United States, probably due to larger moving costs and an individual's dislike of living far away from home. For example, Llull (2016) estimated that the stock of Mexican immigrants in the U.S. would increase by a percentage three times larger than the percentage increase in the stock of Chinese immigrants following a $1,000 increase in U.S. income per capita.

where p_t^s is the index value for state s at time t. $conflict_{t-10,t}^m$ is the casualties from all active conflict events between time t and a decade prior in Mexican state m. $Max.conflict_{t-10,t}$ is the maximum number of casualties from all active conflicts between time t and a decade prior. Thus, $\frac{conflict_{t-10,t}^m}{Max.conflict_{t-10,t}}$ is a normalized conflict measure between time t and a decade prior in Mexican state m with a value between zero and one. $Dist_{sm}$ is the distance of Mexican state m with U.S. state s.[18] Therefore, $\frac{Min.Dist.}{Dist_{sm}}$ is similar to inverse distance weight, but the value is normalized to be between zero and one by multiplying it with the closest distance between a U.S. state and a Mexican state.[19] It follows that the variation in push instrument p_t^s across U.S. states comes from the differences in distance from the place of conflict in Mexico. For ease of interpretation, I standardized the push instrument to have mean of zero and standard deviation of one.

Table 2.8 shows the first stage results of the two IV approaches. Both the network and push instrument are sufficiently strong with robust F-statistics of 66.12 and 17.07, respectively, which is well above the Staiger and Stock (1994) rule of thumb of 10. The interpretation of the push instrument is that a one standard deviation increase in the push index is expected to increase the share of undocumented immigrants by approximately 0.09 percentage points.

The results of the analysis are reported in Table 2.9 through 2.11. Focusing on violent crime rate, I find no evidence that undocumented immigration increases the overall violent crime rate (Table 2.10). The estimates obtained from network instrument suggests that a one percentage point increase in the share of undocumented immigrants in the population is associated with 5% decrease in overall violent crime rate, while the estimates obtained from push instrument are less precise, but nonetheless still show that undocumented immigration is not statistically significantly associated with an increase in violent crimes. In Table 2.10, I report the results of the analysis when violent crimes are disag-

[18]Distance between Mexican state m and U.S. state s is measured by the distance between the most populated city in Mexican state m and the most populated city in U.S. state s.

[19]The closest distance between a U.S. state and a Mexican state in the analysis is the distance between California and Baja California.

gregated into murder, rape, robbery, and aggravated assault. Focusing on the estimates obtained through network instrument, I found that undocumented immigration is statistically significantly associated with an increase in murder rate but negatively associated with rape and aggravated assault. One percentage point increase in the share of undocumented immigrants in the population is associated with 5.9% increase in the murder rate, while it is associated with 7.1% and 8.5% decrease in rape and aggravated assault rates. None of the estimates obtained from push instrument is statistically significant, except for robbery. One percentage point increase in the share of undocumented immigrants in the population is associated with 33.5 more robberies per 100,000 population. However, this result does not hold when the robbery rate is measured in logs. Taken as a whole, the overall evidence suggests a weak association between undocumented immigration and violent crimes, similar to the findings of Light and Miller (2018) who also examine the association between undocumented immigration and violent crimes using different methodology to this study.

Although there is a weak association between undocumented immigration and violent crimes, this result does not naturally extend to property crimes. Undocumented immigrants have more limited labor market opportunities compared to other U.S. residents, mainly because of their illegal status. It is likely, therefore, that they are more vulnerable of committing crimes for financial gains, rather than “crimes of passion” (violent crimes). To examine this, I repeat the analysis above on the property crime rates (Table 2.11). Contrary to the expectation, the results of the analysis show no strong evidence linking undocumented immigration with property crimes. On overall property crime rate, the result obtained from push instrument suggest that one percentage point increase in the share of undocumented immigrants in the population lowers property crime rate by 8.6%, but this estimate is imprecisely estimated and not significant at conventional levels. The result from using past settlement of immigrants as instrument shows that undocumented immigration is not statistically significantly associated with overall property crime rate, corroborating the result obtained from the push instrument. Disaggregating property crimes into burglary, larceny, and motor vehicle theft, the results show that there is no robust evidence that undocumented immigration is statistically significantly associated with an increase in these crime rates. If any, the result obtained from using network instrument as an IV suggests that one percentage point increase in the share of undocumented immigrants in the population is associated with a decrease of burglary rate by 2.9% or 20 less burglaries per 100,000 population when the burglary rate is measured in level.

As a final note, there are some instances in which the estimates obtained from using network instrument present contradictory findings as compared to the ones obtained through push instrument. For example, undocumented immigration is associated with a reduction in rape crime rate when network instrument is used in the analysis, while it is positive and statistically indistinguishable from zero when push instrument is used. My preferred estimates are the ones obtained from using push instrument, not only because it is constructed without relying on past settlement of immigrants, which has been shown to be unlikely to meet the exclusion restriction requirement for a valid IV, but also because it identifies the effect of an increase in the share of undocumented immigrants in the population that comes through the increase in unauthorized Mexican immigrants, which is the focus of recent policy debates. Nonetheless, the overall evidence from the analysis shows a weak link between undocumented immigration and crimes.

2.4 Conclusion

Crimes are costly for society. At the same time, there are concerns that an increase in undocumented immigration may lead to a sizable increase in the crime rates. In this article, I examine the institutionalization (incarceration) rate of undocumented immigrants and quantify the change in crime rates attributable to undocumented immigration.

The analysis yields a few main findings. First, despite possessing many characteristics usually associated with crime, undocumented immigrants are approximately 33% less likely to be institutionalized compared to U.S. natives. Second, there is no evidence that undocumented immigrants who have spent more time in the U.S. are more likely to be institutionalized compared to those who have been in the U.S. for a shorter time. There is evidence, however, that arriving at a younger age is associated with higher institutionalization rate. Finally, overall property and violent crime rates across U.S. states are not statistically significantly increased by undocumented immigration.

2.5 Tables and Figures

Table 2.1: Descriptive Statistics

	All	U.S. Natives	Legal Immigrant	Undocumented Immigrant
Share of All Individuals	-	0.83	0.09	0.09
Years in the U.S.	-	-	15.28	9.47
Institutionalization Rate	0.03	0.03	0.01	0.02
Age	28.73	28.36	31.22	29.73
Race:				
Asian	0.06	0.02	0.27	0.16
White	0.71	0.76	0.44	0.48
Black	0.13	0.14	0.10	0.05
Hispanic Origin	0.16	0.11	0.29	0.50
Education:				
High School Dropout	0.15	0.12	0.20	0.42
High School Graduates	0.30	0.31	0.24	0.26
College	0.55	0.57	0.56	0.32
Observations	4,242,790	3,605,670	335,715	301,405

Source: Author's calculations from ACS 2006 - 2015.

Notes: The table report the summary statistics of men aged 18 to 40 by their residency status. ACS sampling weight is used in the analysis.

Table 2.2: Estimates for Institutionalization Rate

	(1)	(2)	(3)	(4)	(5)
Undocumented Immigrant	-0.011	-0.013	-0.028	-0.026	-0.027
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Legal Immigrant	-0.021	-0.022	-0.023	-0.025	-0.026
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Controls:					
Age	No	Yes	Yes	Yes	Yes
Education	No	No	Yes	Yes	Yes
Race	No	No	No	Yes	Yes
State x Years FE	No	No	No	No	Yes
Observations	4,242,790				

Source: Author's calculations.

Notes: The table reports the difference in institutionalization rate relative to U.S. natives among men aged 18 to 40. Clustered robust standard error at the state level in parentheses. p-value in the brackets. ACS sampling weight is used in the analysis.

Table 2.3: Institutionalization Rate of Undocumented Immigrants Relative to Legal Immigrants

	(1)	(2)
Undocumented Immigrant	0.006	0.009
	(0.002)	(0.002)
	[0.005]	[0.000]
Controls:		
Age	Yes	Yes
Education	Yes	Yes
Race	Yes	Yes
State x Years FE	Yes	Yes
Country of Origin	Yes	Yes
Years Since Migration	No	Yes
Observations	637,120	

Source: Author's calculations.

Notes: The table reports the difference in institutionalization rate relative to legal immigrants among men aged 18 to 40. Clustered robust standard error at the state level in parentheses. *p*-value in the brackets. ACS sampling weight is used in the analysis.

Table 2.4: Assimilation and Age at Arrival Effects (Undocumented Immigrants)

	2007 ACS	2011 ACS	2015 ACS	Assimilation Effects (2007 - 2015)
1991 to 1994 Cohort	-0.015	-0.019	-0.018	-0.003
	(0.010)	(0.009)	(0.007)	[0.765]
	[0.179]	[0.055]	[0.026]	
1995 to 1998 Cohort	-0.019	-0.021	-0.022	-0.003
	(0.011)	(0.009)	(0.008)	[0.770]
	[0.123]	[0.061]	[0.016]	
1999 to 2002 Cohort	-0.018	-0.017	-0.019	-0.001
	(0.011)	(0.010)	(0.008)	[0.934]
	[0.170]	[0.113]	[0.041]	
2003 to 2006 Cohort	-0.014	-0.016	-0.020	-0.005
	(0.012)	(0.010)	(0.009)	[0.697]
	[0.295]	[0.153]	[0.051]	
2007 to 2010 Cohort		-0.003	-0.002	
		(0.011)	(0.009)	
		[0.820]	[0.803]	
2011 to 2014 Cohort			0.013	
			(0.010)	
			[0.217]	
Age at Arrival	-0.001	-0.001	-0.001	
	(0.000)	(0.000)	(0.000)	
	[0.075]	[0.094]	[0.016]	

Source: Author's calculations.

Notes: The table reports the difference in institutionalization rate of undocumented immigrants for a given cohort relative to U.S. natives among men aged 18 to 40. 'Assimilation Effects' column reports the within-cohort difference in relative institutionalization rate of undocumented immigrants in 2015 with its level in 2007. The regressions control for education and age. Clustered robust standard error at the cohort level in parentheses. p-value in the brackets. The p-value in assimilation effects column is based on the hypothesis testing that the difference in the estimate between the third and the first column is equal to zero. ACS sampling weight is used in the analysis.

Table 2.5: Assimilation and Age at Arrival Effects (Naturalized Citizens)

	2007 ACS	2011 ACS	2015 ACS	Assimilation Effects (2007 - 2015)
1991 to 1994 Cohort	0.001	-0.011	-0.010	-0.011
	(0.004)	(0.002)	(0.002)	[0.034]
	[0.786]	[0.000]	[0.000]	
1995 to 1998 Cohort	0.003	-0.005	-0.007	-0.010
	(0.004)	(0.002)	(0.002)	[0.099]
	[0.529]	[0.040]	[0.005]	
1999 to 2002 Cohort	0.004	-0.004	-0.007	-0.011
	(0.005)	(0.003)	(0.003)	[0.113]
	[0.468]	[0.133]	[0.016]	
2003 to 2006 Cohort	0.015	-0.004	-0.003	-0.018
	(0.005)	(0.003)	(0.003)	[0.037]
	[0.032]	[0.259]	[0.405]	
2007 to 2010 Cohort		-0.001	0.000	
		(0.003)	(0.004)	
		[0.729]	[0.976]	
2011 to 2014 Cohort			0.000	
			(0.004)	
			[0.922]	
Age at Arrival	-0.001	-0.001	-0.001	
	(0.000)	(0.000)	(0.000)	
	[0.001]	[0.000]	[0.000]	

Source: Author's calculations.

Notes: The table reports the difference in institutionalization rate of naturalized citizens for a given cohort relative to U.S. natives among men aged 18 to 40. 'Assimilation Effects' column reports the within-cohort difference in relative institutionalization rate of naturalized citizens in 2015 with its level in 2007. Clustered robust standard error at the cohort level in parentheses. The regressions control for education and age. p-value in the brackets. The p-value in assimilation effects column is based on the hypothesis testing that the difference in the estimate between the third and the first column is equal to zero. ACS sampling weight is used in the analysis.

Table 2.6: Cohort Effects

	(1)
Arrival Cohort:	
2011-2014 (ACS 2015) vs 2003-2006 (ACS 2007)	0.028
	[0.103]
2007-2010 (ACS 2015) vs 1999-2002 (ACS 2007)	0.015
	[0.272]
2003-2006 (ACS 2015) vs 1995-1998 (ACS 2007)	0.000
	[0.980]
1999-2002 (ACS 2015) vs 1991-1994 (ACS 2007)	-0.004
	[0.721]

Source: Author's calculations.

Notes: The table reports across cohort difference in the relative institutionalization rate of undocumented immigrants among men aged 18 to 40. The regressions control for education and age. p-value in the brackets. The p-value is based on the hypothesis testing that the difference in the estimate between the recent cohort and the earlier cohort is equal to zero. ACS sampling weight is used in the analysis.

Table 2.7: Assimilation and Age at Arrival Effects (Undocumented Immigrants) Using Legal Immigrants as Reference Group

	2007 ACS	2011 ACS	2015 ACS	Assimilation Effects (2007 - 2015)
1991 to 1994 Cohort	0.015	0.008	0.015	0.000
	(0.000)	(0.001)	(0.002)	[0.823]
	[0.000]	[0.000]	[0.000]	
1995 to 1998 Cohort	0.007	0.004	0.006	-0.001
	(0.000)	(0.001)	(0.001)	[0.492]
	[0.000]	[0.002]	[0.002]	
1999 to 2002 Cohort	0.005	0.004	0.004	-0.001
	(0.001)	(0.001)	(0.001)	[0.486]
	[0.000]	[0.003]	[0.020]	
2003 to 2006 Cohort	0.005	0.001	-0.001	-0.006
	(0.001)	(0.001)	(0.001)	[0.014]
	[0.004]	[0.340]	[0.659]	
2007 to 2010 Cohort		0.005	0.003	
		(0.001)	(0.001)	
		[0.005]	[0.037]	
2011 to 2014 Cohort			0.006	
			(0.001)	
			[0.000]	
Age at Arrival	-0.001	0.000	0.000	
	(0.000)	(0.000)	(0.000)	
	[0.005]	[0.001]	[0.000]	

Source: Author's calculations.

Notes: The table reports the difference in institutionalization rate of undocumented immigrants for a given cohort relative to legal immigrants among men aged 18 to 40. 'Assimilation Effects' column reports the within-cohort difference in relative institutionalization rate of undocumented immigrants in 2015 with its level in 2007. The regressions control for education and age. Clustered robust standard error at the cohort level in parentheses. p-value in the brackets. ACS sampling weight is used in the analysis.

Table 2.8: First Stage Estimates

	Estimates	Robust F-Statistics	Observations
Network Instrument	0.441	66.12	816
	(0.054)		
	[0.000]		
Push Instrument	0.088	17.07	816
	(0.021)		
	[0.000]		

Source: Author's calculations.

Notes: State and year fixed effects along with state-specific time trends are included in the regressions. Regressions are weighted by state population. Clustered robust standard error in parentheses. p-value in the brackets.

Table 2.9: The Effect of Undocumented Immigration on Overall Crime Rate

Type of Crime	OLS		IV Network Instrument		IV Push Instrument	
	Logs	Levels	Logs	Levels	Logs	Levels
Violent Crime	-0.006	-1.500	-0.050	-27.586	-0.015	0.210
	(0.011)	(6.264)	(0.011)	(4.695)	(0.083)	(40.514)
	[0.626]	[0.812]	[0.000]	[0.000]	[0.860]	[0.996]
Property Crime	0.007	34.437	-0.001	13.745	-0.086	-200.350
	(0.010)	(32.927)	(0.012)	(41.842)	(0.112)	(347.786)
	[0.440]	[0.301]	[0.965]	[0.743]	[0.440]	[0.565]
Observations	816		816		816	

Source: Author's calculations.

Notes: The table reports the result of least squares and IV regressions on overall crime rates. 'Logs' estimates report the effect of a one percentage point increase in the share of undocumented immigrants on the log of number of crimes per 100,000 population. 'Levels' estimates report the effect of a one percentage point increase in the share of undocumented immigrants on the number of crimes per 100,000 population. State and year fixed effects along with state-specific time trends are included in the regressions. Regressions are weighted by state population. Clustered standard error at the state level in parentheses. p-value in the brackets.

Table 2.10: The Effect of Undocumented Immigration on Violent Crime Rate

Type of Crime	OLS		IV Network Instrument		IV Push Instrument	
	Logs	Levels	Logs	Levels	Logs	Levels
Murder	0.031	0.236	0.059	0.367	0.011	0.053
	(0.018)	(0.119)	(0.018)	(0.100)	(0.081)	(0.509)
	[0.090]	[0.053]	[0.001]	[0.000]	[0.892]	[0.918]
Rape	-0.023	-0.658	-0.071	-2.297	0.064	0.992
	(0.014)	(0.470)	(0.012)	(0.333)	(0.123)	(2.856)
	[0.122]	[0.168]	[0.000]	[0.000]	[0.605]	[0.728]
Robbery	0.002	2.665	0.004	6.487	0.107	33.478
	(0.013)	(2.026)	(0.019)	(3.172)	(0.092)	(18.274)
	[0.877]	[0.194]	[0.830]	[0.041]	[0.246]	[0.067]
Aggravated Assault	-0.007	-3.874	-0.085	-32.866	-0.120	-34.567
	(0.018)	(6.299)	(0.017)	(4.942)	(0.137)	(42.630)
	[0.682]	[0.541]	[0.000]	[0.000]	[0.379]	[0.417]
Observations	816		816		816	

Source: Author's calculations.

Notes: The table reports the result of least squares and IV regressions on each type of violent crime. 'Logs' estimates report the effect of a one percentage point increase in the share of undocumented immigrants on the log of number of crimes per 100,000 population. 'Levels' estimates report the effect of a one percentage point increase in the share of undocumented immigrants on the number of crimes per 100,000 population. State and year fixed effects along with state-specific time trends are included in the regressions. Regressions are weighted by state population. Clustered standard error at the state level in parentheses. p-value in the brackets.

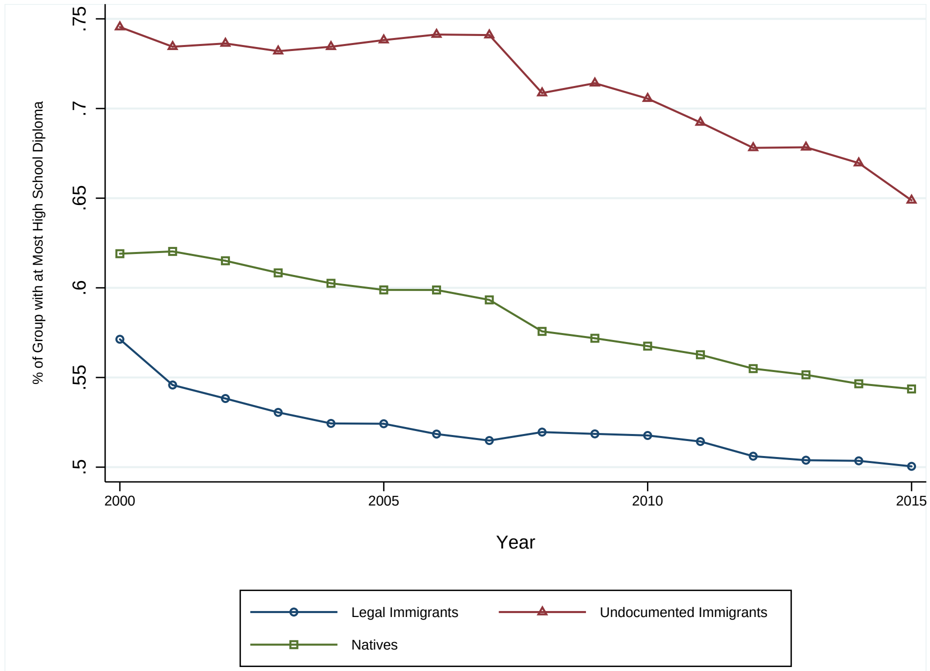
Table 2.11: The Effect of Undocumented Immigration on Property Crime Rate

Type of Crime	OLS		IV Network Instrument		IV Push Instrument	
	Logs	Levels	Logs	Levels	Logs	Levels
Burglary	0.006	9.868	-0.029	-20.240	-0.057	-4.650
	(0.011)	(8.898)	(0.011)	(10.196)	(0.175)	(141.003)
	[0.564]	[0.273]	[0.012]	[0.047]	[0.743]	[0.974]
Larceny	-0.008	-16.299	-0.018	-24.407	-0.108	-157.506
	(0.009)	(23.507)	(0.009)	(23.253)	(0.106)	(202.132)
	[0.364]	[0.491]	[0.045]	[0.294]	[0.310]	[0.436]
Motor Vehicle Theft	0.045	40.760	0.032	58.038	-0.059	-37.550
	(0.022)	(13.638)	(0.035)	(21.510)	(0.085)	(34.379)
	[0.047]	[0.004]	[0.359]	[0.007]	[0.485]	[0.275]
Observations	816		816		816	

Source: Author's calculations.

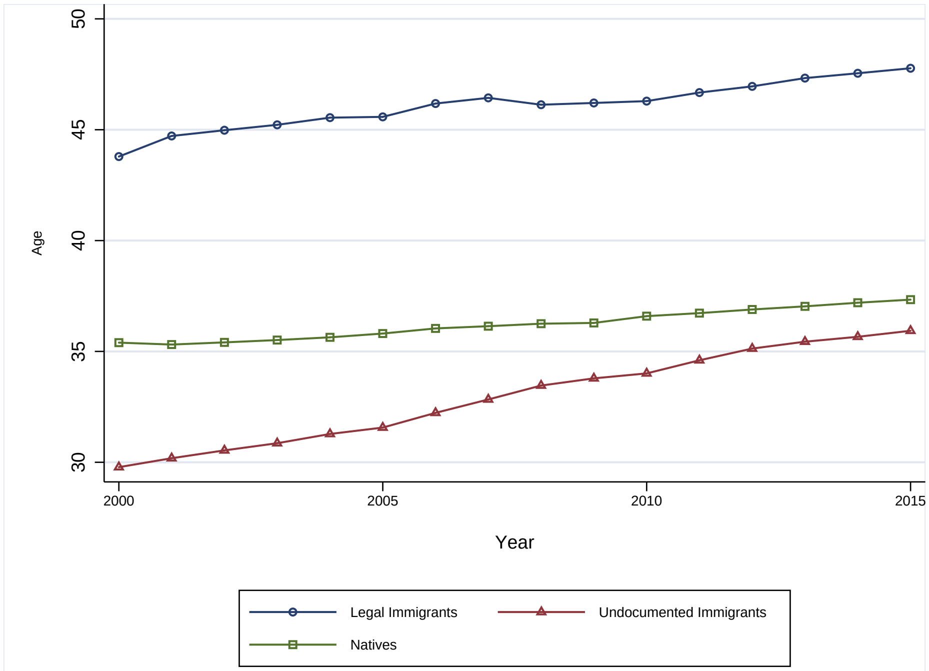
Notes: The table reports the result of least squares and IV regressions on each type of property crime. 'Logs' estimates report the effect of a one percentage point increase in the share of undocumented immigrants on the log of number of crimes per 100,000 population. 'Levels' estimates report the effect of a one percentage point increase in the share of undocumented immigrants on the number of crimes per 100,000 population. State and year fixed effects along with state-specific time trends are included in the regressions. Regressions are weighted by state population. Clustered standard error at the state level in parentheses. p-value in the brackets.

Figure 2.1: Share of Individuals with at Most High School Diploma by Residency Status



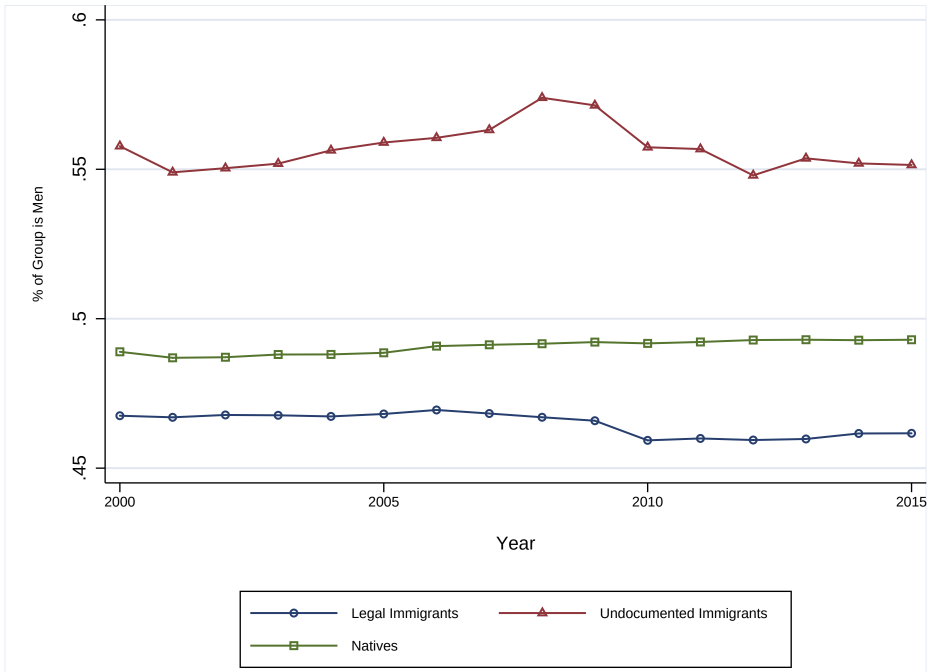
Source: Author's calculation from IPUMS 5% 2000 Census and American Community Survey (ACS) 2001 - 2015. The graph shows the share of individuals with at most high school diploma by residency status over the time period in the analysis. Sampling weight is used in the analysis.

Figure 2.2: Average Age by Residency Status



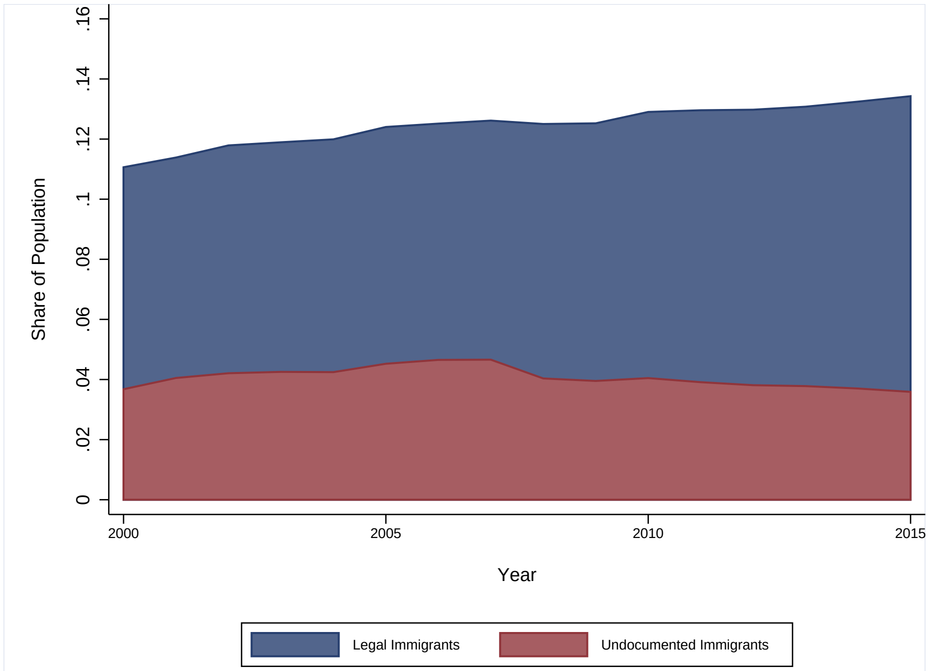
Source: Author's calculation from IPUMS 5% 2000 Census and American Community Survey (ACS) 2001 - 2015. The graph shows the average age of each residency status group over the time period in the analysis. Sampling weight is used in the analysis.

Figure 2.3: Share of Men by Residency Status



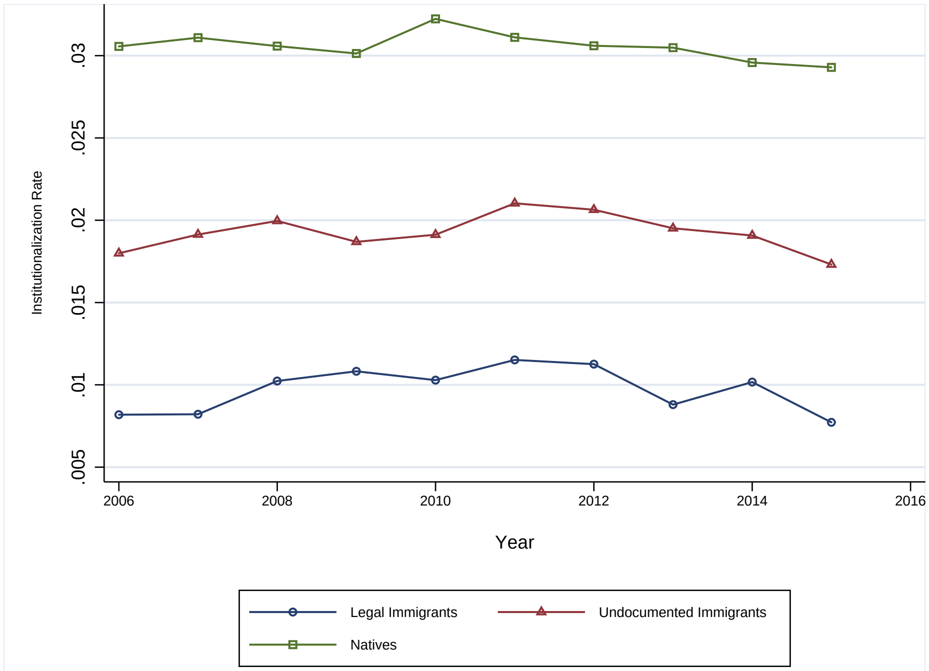
Source: Author's calculation from IPUMS 5% 2000 Census and American Community Survey (ACS) 2001 - 2015. The graph shows the share of men in each residency status group over the time period in the analysis. Sampling weight is used in the analysis.

Figure 2.4: Share of Undocumented Immigrant as % of Total Foreign-Born



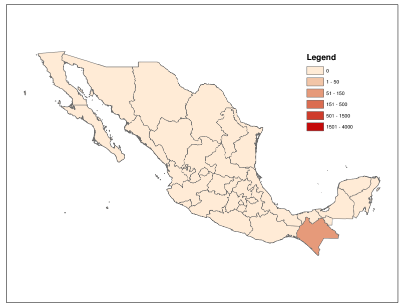
Source: Author's calculation from IPUMS 5% Census 2000 and American Community Survey (ACS) 2001 - 2015. The graph shows the share of undocumented immigrant in the population over the time period in the analysis. Sampling weight is used in the analysis.

Figure 2.5: Institutionalization Rate by Residency Status

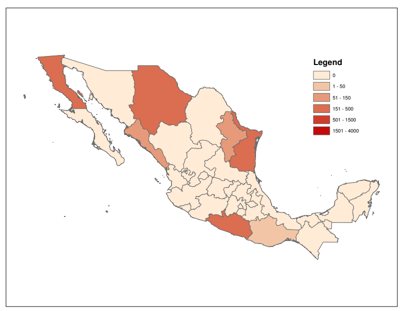


Sources: Author's calculations from American Community Survey 2006 - 2015. The graph shows institutionalization rate of men aged 18 to 40 by their residency status. Sampling weight is used in the analysis.

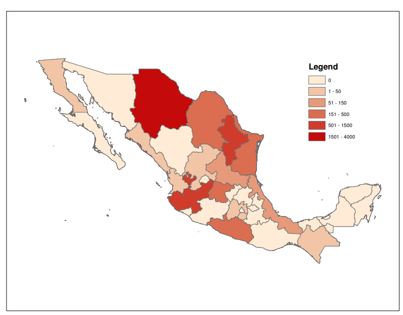
Figure 2.6: Casualties from Active Conflict Events in Mexico 1990 - 2014



1990-1999



2000-2009



2010-2014

Source: Author's calculation from UCDP Georeferenced Event Dataset.

Chapter 3

Immigration and the Health of U.S. Natives

In recent decades, the United States has admitted a large number of foreign-born individuals: their share of the U.S. population increased from 4.7% in 1970 to 13.1% in 2013 (Fry et al., 2015). As such, there is increasing interest in understanding how the United States may benefit from immigration as well as examining its potential associated costs. The economics literature has mainly focused on the wage impact of immigration and the degree of substitution between similarly skilled U.S. and foreign-born workers (e.g., Card, 1990; Borjas, 2003; Ottaviano and Peri, 2012). Despite a multitude of studies on how immigration affects the labor market outcomes of the native population, very little is understood about its effect on the health of U.S.-born individuals.

There are reasons to believe that the influx of immigrants would lead to the deterioration of the health of the native population. For example, immigration may put a strain on the health care system and increase the cost of health care (Borjas and Hilton, 1996), adversely affecting the health of natives. Recently, a study by Giuntella et al. (2018) found evidence of increased outpatient waiting times in economically depressed areas outside of

London, which was attributed to lower mobility among natives in poor neighborhoods and lower health status among immigrants who migrated there.

Although immigration may adversely affect the health status of U.S. natives by increasing pressure on the health care system, an influx of immigrants could also improve the health of natives. Recent studies have documented how immigrants are more likely to be working in risk-intensive, physically demanding occupations compared to natives (Orrenius and Zavodny, 2009, 2013). As such, some scholars have argued that the influx of low-skilled foreign-born workers incentivizes their native counterparts from these occupations toward those with lower physical intensity and risk of injury (Peri and Sparber, 2009; Giuntella et al., 2016). Because working in a risk-intensive or physically demanding occupation is associated with lower health status (Case and Deaton, 2005; Fletcher et al., 2011), an influx of foreign-born workers may improve the health of U.S.-born individuals. Recent studies have also found that low-skilled immigration lowers the expense of immigrant-intensive services such as housekeeping and landscaping (Cortes, 2008), which may improve natives' health due to the availability of these services at a lower cost.[1] Therefore, there is no clear prediction of how immigration would affect the health of the native population.

An important concern in estimating the relationship between immigration and the health of the native population is that immigrants are unlikely to be randomly located across regions. If immigrants are more likely to move to a state with high quality health services, the estimates would spuriously show that immigration improves the health of U.S. natives. To address this concern, I use two approaches. The first approach follows Card (2001) by employing an instrumental variable analysis in which the current location of immigrants from a specific country is predicted using their past location history, usually referred to in the literature as the "network instrument." The instrument intuitively exploits the tendency of immigrants to move into an area where their compatriots reside, mainly

[1]For example, those employed in landscaping experienced 3.5% of total occupational fatalities despite making up only 0.8% of the total U.S. workforce (NIOSH, 2008). Recent work by Cortes and Tessada (2011) has also found that U.S. households are more likely to purchase housekeeping services in response to low-skilled immigration.

because of the lower information cost associated with the migrant network. This approach, however, has been argued to fail to meet the requirement of a valid instrument because factors that have attracted migrants in the past may still be correlated with the outcomes of interest today. To corroborate the results obtained from instrumental variable analysis, the second approach uses the inflow of Cuban refugees in 1995 as a plausibly exogenous shock to investigate how the health of U.S.-born individuals in Miami was affected by this influx. Under the assumption that Cuban refugees chose to migrate to Miami based on reasons unrelated to the health of U.S.-born individuals, this approach would address the concerns of the instrumental variable analysis.

The results of the analysis fail to show that the health of U.S. natives is adversely affected by immigration. Instead, the findings suggest that low-skilled immigration improves the health of low-skilled U.S.-born individuals. A one percentage point increase in the number of low-skilled immigrants relative to the initial population of a state is associated with an approximately 31% decrease in the share of low-skilled U.S.-born men reporting poor health. Furthermore, a one percentage point increase in the number of low-skilled immigrants relative to the initial state population is associated with a 24% decrease in the share of low-skilled U.S.-born men reporting work-related disability. Using Cuban refugee inflow in 1995 as a plausibly exogenous shock to investigate how the health status of U.S.-born individuals in Miami was affected by immigration, the results of the analysis still fail to show that immigration adversely affects the health status of U.S. natives. If anything, the estimate shows that the inflow of Cuban refugees into Miami in 1995 reduced the share of low-skilled U.S.-born men reporting work-related disabilities by 12 percentage points, which corresponds to an approximately 40% decline relative to its value in 1994.

Further extending the analysis, I explore the possible mechanism by which immigration may affect the health of U.S. natives. The fact that immigrants to the U.S. are more likely to hold more difficult jobs than U.S. natives and its role in incentivizing U.S.-born workers toward occupations that are less risk-intensive and physically demanding have been investigated previously (Peri and Sparber, 2009; Orrenius and Zavodny, 2009;

Zavodny, 2015). There are fewer studies, however, that examine how the provision of health care services is affected by immigration in the United States. This issue is particularly relevant for policy makers, especially since the Institute of Medicine has described the problem of crowded emergency rooms in the United States as nearing "the breaking point" (IOM, 2006a). Between 1993 and 2003, the number of patients visiting emergency rooms has risen rapidly from approximately 90.3 to 113.9 million, while the number of hospitals, beds, and emergency rooms has been declining (IOM, 2006b). This has led to low quality care and increased the mortality rate of emergency room centers (Pines and Hollander, 2008; Sun et al., 2013). Immigration could exacerbate the overcrowding problem in emergency rooms by increasing the demand for emergency visits. However, this may not necessarily be the case. A large fraction of physicians (25%) and registered nurses (20%) in the United States are foreign-born (Orrenius et al., 2010). If immigration increases the supply of health resources in the emergency room, it can alleviate the overcrowding problem rather than exacerbate it. Furthermore, studies have documented the lower emergency services utilization rate of immigrants in the United States compared to U.S.-born individuals (Ku and Matani, 2001; Goldman et al., 2006; Cunningham, 2006), suggesting that the crowding effect caused by immigration may not be as large as previously expected.[2] Indeed, the results of the analysis show no robust evidence that immigration exacerbates the overcrowding problem in United States emergency rooms. Although I found that immigration increases the time spent in the emergency room before leaving for an inpatient room, there is no evidence that it increases the waiting time to be seen by health care professionals or the waiting time to be given pain medication for broken bones. Additionally, there is no evidence that immigration lowers the percentage of patients with stroke symptoms receiving brain scan results within 45 minutes of arrival.

[2]It is worth noting that investigations outside the U.S. have found mixed results. For example, a study in Spain by Cots et al. (2007) found that immigrants are more likely to use emergency visits for non-urgent conditions, potentially worsening overcrowding in the emergency room. It should also be noted that under the Emergency Medical Treatment and Active Labor Act (EMTALA), emergency rooms in the United States must provide services regardless of patients' legal status or ability to pay. Nevertheless, immigrants in the United States are less likely to utilize health care services compared to U.S. natives (Ku and Matani, 2001).

This paper contributes to a few studies that attempt to examine the impact of immigration on the well-being of the native population. Indeed, the literature on this topic is still relatively scarce. Recent studies such as Betz and Simpson (2013) and Akay et al. (2014) have found that immigration is positively associated with the subjective well-being or happiness of the native population in Europe. A closely related paper to this study is Giuntella and Mazzonna (2015), who found that in Germany immigration reduces the likelihood of natives to report doctor assessed disability by improving their working conditions. This paper complements the work of Giuntella and Mazzonna (2015) by analyzing the relationship between immigration and the health outcomes of the native population in the United States, using the Cuban refugee inflow in 1995 as a plausibly exogenous shock to examine the validity of the findings obtained from network instrument analysis.

This paper also contributes to the literature that investigates the determinants of emergency room crowding. Previous studies have identified non-urgent visits, inadequate staffing, and hospital bed shortages as the predominant factors that may cause crowding (Derlet and Richards, 2008; Hoot and Aronsky, 2008; Harris and Sharma, 2010). Although the evidence is weak, the results in this study suggest immigration as another probable cause of overcrowding. However, it is worth noting that a more generous immigration policy that allows more of qualified physicians, nurses, and medical staff to enter the U.S. may actually help to alleviate the crowding problem in emergency rooms.

This paper is constructed as follows: Section 2 describes the methodology used in the empirical analysis; Section 3 outlines the data used in the analysis along with descriptive statistics; Section 4 documents the results of the analysis; Section 5 concludes.

3.1 Empirical Methodology

Currently, there are different views in the literature on the best way to measure immigrants' supply shock. Following the work of Borjas (2003), previous studies (e.g., Akay et al., 2014; Giuntella and Mazzonna, 2015) have mainly used the population share of immigrants as the measure of their supply shock. The use of this measure, however, has been argued to lead to biased estimates: the change in the population share of immigrants is determined not only by immigrants' influx but also the change in the number of natives in the population (Card and Peri, 2016). This concern is particularly acute if the dependent variable considered in the analysis is related to outcomes regarding the native population. If an improvement in health care services induces more U.S. natives to migrate to a particular location, the estimates obtained from using the share of immigrants in the population as the measure of immigrants' supply shock would spuriously show that immigration adversely affects the health of U.S. natives. Therefore, I adopt empirical specifications similar to Basso and Peri (2015), which address the concern outlined by Card and Peri (2016):

$$\Delta ln(y_{st}) = \alpha_0 + \alpha_1 \frac{\Delta Immigrant_{st}}{Population_{s,t-1}} + \delta_s + \delta_t + \varepsilon_{st} \tag{3.1}$$

where y_{st} is the outcome of interest in state s at time t. δ_s and δ_t are state and period fixed effects, respectively. Because the sample consists of multiple time periods, δ_s controls for state-specific growth rates.[3] In other words, the specification considers that some states may experience a higher level of improvement in natives' health outcomes compared to other states.[4] The coefficient of interest is α_1, which shows the percent change in the outcome variable following a one percentage point increase in the number of immigrants relative to the initial population (in the previous year). I limit the analysis to U.S.-born individuals aged 18 to 64 to avoid the potential bias associated with changes in perceived/actual health status after retirement (Coe and Zamarro, 2011; Mazzonna and Peracchi, 2012).[5] Additionally, I conduct the analysis at the state level to minimize bias caused by measurement error and the migration response of natives to the inflow of immigrants.[6] I consider three health

[3]As noted by Hines and Peri (2019), the area fixed effects in the empirical specifications in which the dependent variable is expressed in annual changes capture location-specific trends.

[4]For example, in recent years, some states have expanded their Medicaid programs. If immigrants are attracted to the locations where natives' health outcomes improved the most, it will create a false correlation between immigration and natives' health. The inclusion of state fixed effects in equation 1 addresses this concern by taking into account how natives' health outcomes in each state could be on different trajectories.

[5]The sample used includes all natives aged 18 to 64 regardless of their labor force status.

[6]For example, it is harder for natives to move to other states than to move to another city within a state

outcomes in my analysis: the share of U.S.-born individuals reporting poor health, the share of U.S.-born individuals claiming work-related disability, and the share of U.S.-born individuals who declare that they have ever quit a job for health reasons.

For overcrowding outcomes, there is no single indicator that best characterizes emergency room overcrowding. The health literature has considered the waiting time to first contact with a physician, the time from triage to care, delays in the transfer of admitted patients from emergency rooms, and ambulance diversion as indicators to measure overcrowding (Lambe et al., 2003; Schneider et al., 2003; McCarthy et al., 2009; Hwang et al., 2011). Following previous studies, and given the availability of data, I consider the following proxies to measure overcrowding in emergency rooms: median time (in minutes) patients spent in an emergency room before they were seen by a health care professional, median time (in minutes) patients spent in an emergency room after being admitted as an inpatient before leaving for their inpatient room (i.e., boarding time), the median time (in minutes) patients who came to the emergency room with broken bones had to wait before receiving pain medication, and the percentage of patients who arrived at the emergency room with stroke symptoms and then received brain scan results within 45 minutes.

As noted above, one concern with estimating equation (1) using a simple least-squares approach is that immigrants are not randomly located across U.S. states. If foreign-born individuals choose to locate to a state where the quality of health care is better relative to others, the estimates would falsely show that immigration is associated with less emergency room overcrowding and the better health of natives. To mitigate the potential bias associated with this issue, I use an instrumental variable approach based on the work of Card (2001). The instrument exploits the tendency of immigrants to move to areas with a higher density of their compatriots, partly because of the lower information costs associated with ethnic networks. Formally, the instrument is constructed as follows:

in response to the influx of immigrants. These concerns are outlined by Borjas (2006) and Aydemir and Borjas (2011) in the context of the wage effect of immigration.

$$\frac{\Delta \widehat{Immigrant}_{st}}{\widehat{Population}_{s,t-1}} = \frac{\widehat{Imm}_{s,t} - \widehat{Imm}_{s,t-1}}{\widehat{imm}_{s,t-1} + Native_{s,t-1}} \quad \text{where} \quad \widehat{Imm}_{st} = \sum_{c=1}^{9} Imm_{ct} \times \frac{Imm_{cs,1970}}{Imm_{c,1970}}$$

where $Native_{s,t-1}$ is the total number of U.S.-born individuals in state s at time $t-1$. $\widehat{Imm}_{st}$ is the predicted number of immigrants in state s at time t. Imm_{ct} represents the total number of immigrants from country of origin c at time t.[7] $\frac{Imm_{cs,1970}}{Imm_{c,1970}}$ represents the share of immigrants from country c who were living in state s in 1970. $\widehat{Population}_{s,t-1}$ represents the predicted population size of state s at time $t-1$ obtained by adding the predicted number of immigrants to the sum of the U.S.-born population in the state.

The instrument would be valid under the assumption that factors that have attracted migrants to a particular destination in the past are not correlated with the outcome of interests in the destination today. A recent study by Jaeger et al. (2018) points out that the use of network instruments in specifications similar to equation (1) to estimate the wage effect of immigration is likely to be biased because it does not take into account the long-run adjustments associated with immigration (e.g., capital adjustment).[8] In my case, I would be less likely to find that immigration leads to overcrowding or the deterioration of natives' health status if more health resources (e.g., hospitals, clinics, and beds) are being provided in the state in the long run as a response to the arrival of immigrants.

[7] Following Spenkuch (2013), I aggregate countries into nine groups: North-western Europe, Eastern Europe, Southern Europe, Asia, Mexico, South and Central America, Africa, Canada, and all other countries.

[8] A number of recent studies have also examined the identifying assumption of the network instrument. A study by Goldsmith-Pinkham et al. (2018) argues that the sufficient condition for the network instrument to satisfy the exclusion restriction requirement is the exogeneity of immigrants' shares; that is, states with different initial stocks of immigrants in 1970 would have evolved in a similar way in the absence of immigration. They propose a test to examine the correlation between the initial shares that account for much of the key variation and the states' observed characteristics in the base year. Since Europe was the largest immigrant-sending region to the U.S. in 1970 (Pew, 2015), I use European immigrant shares in the analysis. The results of the analysis are reported in Appendix Table 3.11. Indeed, the European immigrant shares are statistically significantly correlated with many states' characteristics, including the share of Blacks and the share of married individuals in the population, suggesting that the initial immigrant shares may not be exogenous. However, it is worth noting that the work by Borusyak et al. (2018) argues that when the exogeneity of the shares is not satisfied, the exclusion restriction requirement for the network instrument will be met if there are many independent random shocks affecting the flows of migration from the country of origin to the United States. Additionally, the results from the 1995 Cuban refugee inflow analysis support the findings resulting from the use of the network instrument as an IV.

To corroborate the findings obtained from network instrument analysis, I use Cuban refugee inflow in 1995 as a plausibly exogenous shock to examine how the health outcomes of U.S. natives in Miami were affected by this influx. Considering the exogenous nature of Cuban refugee inflow in 1995, this approach would address the concerns of using the network instrument in an instrumental variable analysis. Unfortunately, the data for emergency room overcrowding measures are only available since 2012, which prevents me from examining whether the inflow of Cuban refugees in 1995 exacerbated emergency room overcrowding in Miami. Nonetheless, I am able to investigate how the health of U.S.-born individuals in Miami changed following the arrival of Cuban refugees in 1995.

3.2 Data and Descriptive Statistics

To construct the share of U.S-born individuals reporting poor health, I use the respondents' answer to the health status question on the Annual Social and Economics Supplement of the Current Population Survey (CPS-ASEC) from 2000–2016 available from Ruggles et al. (2015).[9] The health status indicates an individual's health on a five-point scale: excellent (5), very good (4), good (3), fair (2), and poor (1). The CPS-ASEC also asks whether an individual has "a health problem or a disability which prevents him/her from working or which limits the kind or amount of work," which I use to construct the share of U.S. natives reporting work disability. Additionally, the CPS-ASEC reports whether an individual has "ever retired or left a job for health reasons," which I use to construct the share of U.S. natives reporting that they have quit a job because of health reasons.

Finally, the foreign-born population of the state is constructed using data from the IPUMS 5% 2000 Census and ACS 2001–2016.[10] To construct the network instrument's

[9]For the 2014 CPS ASEC sample, the Census Bureau administered a redesigned income questionnaire randomly to 3/8ths of the sample. The sampling weight in this year was designed such that either the 3/8ths group or the group who did not receive the redesigned questionnaire is independently representative of the entire U.S. population. I divide the individuals' sampling weight for the 2014 CPS-ASEC by two so that it is representative of the entire U.S. population while using all observations available for that year.

[10]The Census Bureau collects information from all immigrants regardless of their legal status. As such, foreign-born individuals in the sample include both those who are legally in the U.S. and undocumented immigrants. It is possible to construct the foreign-born population using IPUMS CPS-ASEC data starting

initial immigrant shares in 1970, I use the IPUMS 1% 1970 Census. Following the literature, I classify immigrant/foreign-born individuals as those who are naturalized or non-citizens. There is no restriction on age in the construction of immigrants' supply shock measures. The summary statistics are reported in Table 3.1. On average, U.S. states have more low-skilled U.S. natives with no high school diploma reporting poor health than high-skilled natives with at least a high school diploma. Similarly, there are more low-skilled U.S. natives reporting work-related disabilities than high-skilled natives on average. In a subsequent analysis, I will also examine how the health outcomes of U.S. natives in Miami were affected by the Cuban refugee inflow in 1995. The data used in that analysis is obtained from CPS ASEC 1994-1999. Throughout the analysis, low-skilled refers to individuals with no high school diploma while high-skilled refers to persons with at least a high school diploma.

I obtained the state-level measures of emergency room overcrowding from the Center for Medicare and Medicaid Services.[11] The data on timely and effective care in emergency rooms is available only from 2012, which limits the analysis period concerning emergency room overcrowding to 2012 to 2016. The 2012–2016 period in the sample was characterized by an improvement in the emergency room overcrowding problem in the United States (Figure 3.1). The median time a patient in the emergency room has to wait before being seen by a health care professional falls by eight minutes, a 26% declines relative to its level in 2012. Similarly, the median time a patient in the emergency room with broken bones has to wait before being given pain medication also drops by ten minutes, a 16% improvement compared to 2012. A majority (∼70%) of patients in emergency rooms with stroke symptoms received brain scan results within 45 minutes of arrival in 2016, an approximately 66% increase relative to its level in 2012. The only measure that shows no improvement is the boarding time. At the median, a patient needs to wait in the emergency

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from 1994. However, the sample size in CPS-ASEC is much smaller than the IPUMS 5% 2000 Census and ACS data. One concern is that using CPS-ASEC to construct the measure of immigrant supply shock would attenuate the impact of immigration. Indeed, the study by Aydemir and Borjas (2011) found that bias from sampling error in the measure of immigrant supply shock severely attenuates the wage effects of immigration.

[11] Available from https://data.medicare.gov/data/archives/hospital-compare.

room for approximately 98 minutes after being admitted as an inpatient before leaving for his/her inpatient room.

3.3 Results

3.3.1 Immigration and the Health of U.S. Natives

The main mechanism by which immigration imparts health benefits upon U.S. natives is by incentivizing U.S.-born workers to less risk-intensive or physically demanding occupations. This means that low-skilled immigration should benefit the health of U.S. natives more than high-skilled immigration, since low-skilled immigrants are more likely to take on physically demanding work compared to high-skilled immigrants. In Table 3.2, I report the impact of low-skilled immigration on the share of natives reporting poor health. The results suggest that one percentage point increase in the number of low-skilled immigrants with no high school diploma relative to the initial population is associated with a 24% decline in the share of low-skilled U.S.-born men reporting poor health. The IV model suggests that if anything this estimate is conservative.[12]

In Table 3.3, I report the results for work-related disability. Focusing on the IV estimates, the results suggest that a one percentage point increase in the number of low-skilled immigrants relative to the initial population is associated with a 24% and 28% decrease in the share of low-skilled U.S.-born men and women reporting work-related disabilities, respectively. Although the magnitude of these effects might seem large, it is comparable to the estimate found by Giuntella and Mazzonna (2015), who found that a one percentage point increase in the population share of immigrants in the United Kingdom reduces the risk of a doctor-assessed disability by approximately 25%. The results for the share of natives reporting that they have ever quit a job because of health reasons supports the previous

[12]The instrument for low-skilled immigration is constructed analogously to equation 2 as follow: $\frac{\Delta \widehat{Immigrant}^{LS}_{st}}{\widehat{Population}_{s,t-1}} = \frac{\widehat{Imm^{L}_{s,t}}S - \widehat{Imm^{LS}_{s,t-1}}}{\widehat{imm}_{s,t-1} + Native_{s,t-1}}$ where $\widehat{Imm^{LS}_{st}} = \sum_{c=1}^{9} Imm^{LS}_{ct} \times \frac{Imm^{LS}_{cs,1970}}{Imm^{LS}_{c,1970}}$. LS denotes low-skilled. I construct the instrument for high-skilled immigration in a similar way.

findings (Table 3.4). The OLS estimates suggest that a one percentage point increase in the number of low-skilled immigrants relative to the initial population is associated with a 28% and 26% reduction of low-skilled U.S.-born men and women reporting that they have ever quit a job because of health reasons, respectively.[13] Similar to the above, the IV model suggests that if anything these estimates are conservative.[14]

Since the health benefits from immigration come mainly from incentivizing U.S. natives into less physically demanding occupations, there should be smaller health benefits for U.S.-born workers from an inflow of high-skilled immigrants with at least a high school diploma. The results reported in Tables 3.5 to 3.7 suggest that this is indeed the case. Most of the estimates are smaller in magnitude and not statistically significant, suggesting that high-skilled immigration does not improve nor adversely affect the health of U.S. natives in the working-age population.

As a sensitivity check, I examine the robustness of the findings above when economic and demographic controls are included in the estimation. Specifically, Appendix Tables 3.13 to 3.18 depict the results in which I control for the unemployment rate, employment-to-population ratio, the population share of Blacks, the population share of married individuals, and the average age in a particular state. It is worth noting that adding some of these controls may bias the estimates because some are also affected by immigration.[15] Nonetheless, the previous results hold qualitatively.

One important concern is that natives may move to other areas in response to immigration. If natives with poor health are more likely to move to low-immigration areas in response to an inflow of immigrants, the estimates would incorrectly show that immigration

[13] One potential concern is that the effect of low-skilled immigration on the health outcomes of U.S. natives might be driven by the displacement effect. For example, if natives drop out of the labor force in response to immigration, and only those who work report work-related disabilities, the estimates would be biased downward. However, it is worth noting that there is little evidence that the labor force participation of U.S. natives is being adversely affected by immigration (Altonji and Card, 1991; Zavodny, 2018).

[14] I also examine the results when immigrants' shares in the construction of the network instrument used more origin-country groups following (Mayda et al., 2018) as a robustness check. The results of this analysis are reported in Appendix Table 3.12, and the findings are qualitatively similar. Mayda et al. (2018) aggregated countries of immigrants into 14 origin-country groups: Mexico, Canada, Rest of Americas, Western Europe, Eastern Europe, China, Japan, Korea, Philippines, India, Rest of Asia, Africa, Oceania, and Other.

[15] See "bad control" in Angrist and Pischke (2008) for further discussion.

improves the health of natives.[16] The choice of conducting the analysis at the state level should mitigate the bias that arises from this concern, since natives' migration response to an inflow of immigrants at a more aggregate level should be smaller than at a finer level, such as metropolitan statistical areas (MSA). In Appendix Table 3.19, I report the effect of an inflow of low-skilled immigrants on low-skilled natives' out-migration rate.[17] The result suggests that one percentage point increase in the number of low-skilled immigrants with no high school diploma relative to the initial population is associated with an eight percent increase in low-skilled natives' out-migration rate. However, this effect is not statistically significant. This result is consistent with the findings of Card and Peri (2016), who found a sizable increase in natives' migration flows in response to immigration at the MSA level, but it is smaller and not statistically significant at the state level.

It is also important to examine the mechanism behind the findings reported above. Specifically, an inflow of low-skilled migrants induces the native population to move from occupations with a high intensity of manual tasks toward occupations that require greater communication skills (Peri and Sparber, 2009). In Appendix Table 3.20, I replicate the findings of Peri and Sparber (2009) to see if the effect is also observed in the data and period of analysis used in this study.[18] The result suggests that a one percentage point increase in the number of low-skilled immigrants relative to the initial population is associated with a 1.2% increase in the relative task (communication/manual) intensity supplied by the native population. This estimate is larger than the effect found by Peri and Sparber (2009), who estimated that a one percentage point increase in the foreign-born share of low-skilled workers is associated with a 0.37% increase in the relative tasks supplied by the native population. The difference may arise because the estimate in this study is obtained using

[16] Indeed, Giuntella et al. (2018) found that much of the reduction in the waiting times associated with immigration in England can be attributed to natives' migration response to an inflow of immigrants.

[17] Natives' out-migration rate is defined as the number of natives who move out of a state in year t divided by the native population in that state in the previous year ($t-1$).

[18] Peri and Sparber (2009) obtained the manual and communication task intensity for each occupation from the O*Net database. The authors examined how the relative task (communication/manual) intensity supplied by U.S. natives changes in response to low-skilled immigration.

the sample of recent immigrants who are more likely to be different from the native population.[19]

The analysis so far has focused on the working-age population. This choice is made to avoid the potential bias associated with changes in perceived/actual health status after retirement (Coe and Zamarro, 2011; Mazzonna and Peracchi, 2012). However, home care for elderly individuals in the United States largely depends on immigrant labor (Zallman et al., 2019). Therefore, an inflow of immigrants has the potential to improve the health of elderly individuals. In Appendix Tables 3.21 and 3.22, I report the results of the impact of low- and high-skilled immigration on the share of the native population over 64 years old reporting poor health.[20] An interesting finding is that there is evidence that high-skilled immigration improves the health of elderly U.S.-born individuals. A one percentage point increase in the number of high-skilled immigrants with at least a high school diploma relative to the initial population is associated with a 45% and 35% decline in the share of high-skilled U.S.-born men and women over 64 years old reporting poor health, respectively. It is worth noting that this finding does not contradict the previous results since elderly care occupations often require a high school diploma and formal training or certification.[21] In other words, the main mechanism through which immigration affects the health of U.S. natives is likely to differ depending on their working-age status. An inflow of low-skilled immigrants improves the health of working-age U.S. natives mainly by incentivizing them towards less risk-intensive occupations.[22] However, for elderly individuals, the inflow of high-skilled immigrants with at least a high school diploma affects their health outcomes mainly by increasing access to elderly care.

[19]Peri and Sparber (2009) used decennial census from 1960 to 2000 in their analysis. According to Jaeger et al. (2018), 41% of immigrants who arrived in the 1960s were of Canadian or European origin, while only 17% of those arrived in the 1970s were of Canadian or European origin.

[20]In this analysis, I did not examine how immigration affects work-related disability or quitting a job because of health reasons since individuals over 64 years old are likely to be retired and out of the workforce.

[21]See `https://www.bls.gov/ooh/healthcare/home-health-aides-and-personal-care-aides.htm`

[22]It should be noted that low-skilled immigration could also affect the health of U.S. natives by changing their consumption habits. For example, Cortes (2008) found that an inflow of low-skilled immigrants lowers the price of immigrant-intensive services such as housekeeping and landscaping. Since these activities are relatively risk-intensive, an increase in the ability to purchase these services may improve U.S. natives' health.

3.3.2 Evidence from Cuban Refugee Inflow in 1995

As previously noted, the estimates obtained using the network instrument are likely to be biased for two reasons. First, it conflates the short-term effect of immigration with its long-term adjustment (Jaeger et al., 2018). Additionally, factors that have attracted immigrants to a particular location in the past may be correlated with the current outcomes at the destination. In this section, I attempt to validate the findings from the previous section using the 1995 arrival of Cuban refugees in Miami as a plausible exogenous shock.

Initially, the inflow of Cuban refugees into Miami in 1995 was thought as never happened. In a seminal work by Angrist and Krueger (1999), the authors wrote:

> *In the summer of 1994, tens of thousands of Cubans boarded boats destined for Miami in an attempt to emigrate to the United States in a second Mariel Boatlift that promised to be almost as large as the first one, which occurred in the summer of 1980. Wishing to avoid the political fallout that accompanied the earlier boatlift, the Clinton Administration interceded and ordered the Navy to divert the would-be immigrants to a base in Guantanamo Bay. Only a small fraction of the Cuban emigres ever reached the shores of Miami. Hence, we call this event, "The Mariel Boatlift That Didn't Happen."*

As noted by Anastasopoulos et al. (2018), however, the second Mariel Boatlift did take place, although it was delayed by one year. Cuban emigres were allowed into the United States after President Clinton reversed course and permitted their entry in May of 1995. Approximately 75,000 Cubans immigrated to the United States during this event, and the number of high school dropouts in Miami's labor force increased by 5.5% (Anastasopoulos et al., 2018).[23] In Figure 3.2, I show the evolution of the population share of low-skilled

[23] Lending support to the credibility of the second Mariel Boatlift as an exogenous shock, there is evidence that the timing of the shock and the location choice of the Cuban refugees during the second Mariel Boatlift are unrelated to factors that might affect the health of U.S. natives. For example, a New York Times article by Navarro (1996) reports that the majority of Cuban refugees during the second Mariel Boatlift chose to reside in Florida because they had families and friends there. Another article by Greenhouse (1995) suggests that the decision to reverse the policy was based on the concern of a potential riot or civil disturbance at

immigrants in Miami between 1994 and 1999. Indeed, the share of low-skilled immigrants in Miami increased sharply in 1995 and 1996. A peculiar finding is that the peak is observed in the 1996 CPS ASEC. This is because the CPS ASEC survey is usually conducted in March and the decision to reverse the policy occurred in May of 1995. Therefore, the majority of Mariel refugees entering the United States during the second Mariel Boatlift is only observed starting from the 1996 CPS ASEC. Of course, not all Mariel refugees were successfully intercepted, resulting in a smaller observed increase in the share of low-skilled immigrants in Miami in the 1995 CPS ASEC.

I use the data from the CPS-ASEC 1994–1999 to examine how this Cuban refugee influx affected the health of U.S. natives in Miami. The immigrant status information can only be obtained starting from 1994, which prevents me from using earlier years in the analysis. Although I only have one pretreatment year in the analysis, the data does allow me to conduct a simple difference-in-difference estimation to validate the estimates obtained using the network instrument. Additionally, because the 1994 CPS-ASEC was conducted in March, it should preclude the inflow of Cuban emigres who were not intercepted and made it to Miami during or after the summer of 1994. Formally, I consider the following empirical specifications:

$$y_{mt} = \beta_0 + \beta_1(Miami\,x\,Post_{1994}) + Controls_{mt} + \delta_m + \delta_t + \varepsilon_{mt} \tag{3.2}$$

where y_{mt} is the health outcome of the native population of metropolitan area m at time t.[24] $Controls_{mt}$ is the control for metropolitan areas' economic conditions (i.e., unemployment and employment rates). Since the poor health status questionnaire was only available beginning in 1996, I use the share of the native population reporting work-related disabilities and the share of U.S.-born individuals reporting that they have ever quit a job due to health reasons as the outcomes for analysis.

Guantanamo, where the Cubans intercepted at the sea were held.

[24] All metropolitan areas identified in the IPUMS CPS-ASEC 1994–1999 are used in the analysis. Miami is defined as "Miami-Hialeah, FL" (METAREA=5000).

The first stage results depict the effect of the second Mariel Boatlift on the share of low-skilled immigrants in Miami, reported in Table 3.8. The share of low-skilled immigrants in Miami increased by 1.5 percentage points due to the Boatlift, which corresponds to an 8.8% increase relative to its 1994 value. The main findings are reported in Table 3.9. The share of low-skilled U.S.-born men reporting work-related disabilities and those who have ever quit a job because of health reasons fell by 12 percentage points after the event. Overall, there is a lack of evidence that the inflow of Cuban refugees in 1995 worsened the health of U.S. natives in Miami.

One important concern is that the results above may simply be driven by the differential trends between Miami and other metropolitan areas over time. For example, Peri and Yasenov (2019) argue that the findings of Borjas (2017c), who observed that the wages of low-skilled non-Hispanic men in Miami were adversely affected by the first Mariel Boatlift, are sensitive to the choice of pre-treatment period and control group. Data limitation does not allow me to examine if my findings are driven by the differential in pre-trends between Miami and other cities. However, I am able to check the sensitivity of my results using placebo cities (with characteristics similar to Miami) that are used in the literature. In the seminal work by Card (1990), the author used four cities (Atlanta, Los Angeles, Houston, and Tampa-St.Petersburg) as controls because these cities have relatively large Black and Hispanic populations and exhibit a similar economic growth pattern to Miami. In the work of Borjas (2017c), the authors propose an "employment placebo" (Anaheim, Rochester, Nassau-Suffolk, and San Jose) and a "low-skill placebo" (Los Angeles, Houston, Gary, and Indianapolis) based on the similarity in the employment and low-skill employment growth rate between these cities and Miami. The results of these sensitivity checks are reported in Appendix Tables 3.23 to 3.25. Although some of the estimates are imprecise, the sign and the magnitude of coefficient estimates largely mirror the baseline results in which all metropolitan areas are used as control cities.

In sum, the overall evidence from the second Mariel Boatlift is largely in line with the findings from the previous section that there is a lack of evidence that immigration adversely affects the health of U.S. natives. Rather, the results suggest that immigration might improve the health outcomes of U.S. natives, especially those of low-skilled U.S.-born men.

3.3.3 Immigration and Emergency Room Crowding

In this subsection, I examine a possible mechanism through which immigration may adversely affect the health status of the U.S.-born population. The role of immigration in incentivizing U.S. workers from risk-intensive, physically demanding jobs towards occupations with lower physical intensity and risk of injury have been investigated in the literature (Peri and Sparber, 2009; Orrenius and Zavodny, 2009; Zavodny, 2015). However, there are fewer studies that examine how the provision of health care services is affected by immigration to the United States. In the following analysis, I examine whether immigration is associated with overcrowding in emergency rooms across the U.S. states.

Table 3.10 shows the results of the analysis on the effect of immigration on emergency room crowding. Focusing first on the least-squares estimates, the evidence is mixed. Although a one percentage point increase in the number of immigrants relative to the initial population is associated with a reduction in the time before being seen by health care professionals, it is associated with a higher waiting time for pain medication and to leave for an inpatient room. However, none of the estimates are statistically significant at the conventional levels.

Relative to least-squares estimates, the magnitude of the IV estimates are larger in the absolute term for all measures. It is worth noting that the limited period of analysis reduces the strength of the network instrument (Robust F-Statistics of around eight). Therefore, the IV estimates should be interpreted with caution. Nonetheless, the results show no robust evidence that immigration exacerbates the overcrowding problem in emergency rooms. Although I found that a one percentage point increase in the number of immigrants relative to the initial population increases the minutes spent in the emergency room before leaving for an inpatient room by 20%, there is no evidence that immigration statistically significantly increases the wait time before being seen by health care professionals or the wait time before receiving pain medication for broken bones. Furthermore, there is no evidence that immigration statistically significantly reduced the percentage of patients with stroke symptoms receiving brain scan results within 45 minutes of arrivals.[25]

There are a few considerations in interpreting the results from the emergency room overcrowding analysis. First, the time window examined in this analysis is the period when undocumented immigration was declining in the U.S., while there was an improvement in the emergency room overcrowding problem. Therefore, the results may not be generalizable to the period characterized by an increase in undocumented immigration and the worsening of the overcrowding problem in emergency rooms. Additionally, the presence of non-profit community health centers that provide reliable services to many undocumented immigrants might help reduce the pressure on emergency services (Wallace et al., 2016). Nevertheless, the findings from the emergency room overcrowding analysis partly explain why there is a lack of evidence that immigration adversely affects the health of U.S. natives.

3.4 Conclusion

In recent decades, the United States has admitted a large number of foreign-born individuals. As such, there is an interest in understanding how it may benefit from immigration as well as to examine the potential associated costs. In this paper, I examine whether the health of U.S.-born individuals is affected by immigration.

I have reached two main findings. First, the results of the analysis fail to show that the health of U.S.-born individuals is adversely affected by immigration. Instead, the results suggest that low-skilled immigration may improve the health of low-skilled U.S. natives. A one percentage point increase in the number of low-skilled immigrants relative to the initial population is associated with an approximately 31% decline in the share of low-skilled U.S.-

[25]I also explore the possibility that low-skilled immigration might affect emergency room overcrowding differently than high-skilled immigration. However, the instrument in low-skilled immigration analysis is so weak that the model is essentially unidentified. For high-skilled immigration, the results are mixed. The results of this analysis are reported in Appendix Tables 3.26 and 3.27.

born men reporting poor health. Using the Cuban refugee inflow in 1995 as a plausible exogenous shock to validate this finding, I find that the share of low-skilled U.S.-born men in Miami reporting work-related disabilities decreased by 14.6 percentage points following this influx. Second, there is also a lack of evidence that immigration worsens the problem of emergency room overcrowding in the United States, partly explaining why there is no evidence that immigration adversely affects the health of U.S. natives. Taken as a whole, these findings suggest that the health benefits of immigration for U.S.-born individuals may outweigh the costs.

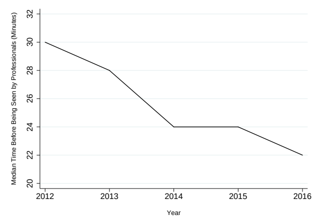
3.5 Tables and Figures

Table 3.1: States' Summary Statistics

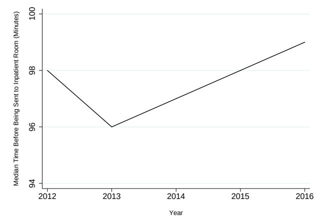
	Mean	SD	Min.	Max.
Share of Natives Reporting Poor Health				
by Gender and Education:				
Male Low-skilled	0.079	0.049	0.000	0.313
Male High-skilled	0.027	0.012	0.004	0.090
Female Low-skilled	0.091	0.047	0.000	0.304
Female High-skilled	0.028	0.011	0.006	0.077
Share of Natives Reporting Work Disability				
by Gender and Education:				
Male Low-skilled	0.195	0.072	0.027	0.465
Male High-skilled	0.081	0.021	0.026	0.152
Female Low-skilled	0.236	0.097	0.020	0.670
Female High-skilled	0.077	0.019	0.027	0.143
Share of Natives Reporting Ever Quit a Job Because of Health Reasons				
by Gender and Education:				
Male Low-skilled	0.071	0.038	0.000	0.246
Male High-skilled	0.038	0.011	0.013	0.088
Female Low-skilled	0.086	0.051	0.000	0.356
Female High-skilled	0.036	0.010	0.014	0.079
Share of Immigrants in Population	0.084	0.060	0.008	0.274
Share of Low-skilled Immigrants in Population	0.030	0.022	0.002	0.130
Share of High-skilled Immigrants in Population	0.054	0.040	0.007	0.174
Emergency Care:				
Median Time (Minutes) Before				
Being Seen by Healthcare Professionals	26.40	7.61	14.00	63.00
Median Time (Minutes) Spent in ED After Being				
Admitted as Inpatient Before Leaving for Inpatient Room	98.09	34.94	39.00	250.00
Median Time (Minutes) Before				
Being Given Pain Medicine for Broken Bones	55.45	8.55	38.00	83.00
Pct. With Stroke Symptoms Received				
Brain Scan Results within 45 Minutes of Arrivals	54.47	14.38	0.00	88.00

Notes: Estimates for poor health status, work disability, and ever quit a job because of health reasons are based on CPS ASEC 2000-2016. Estimates for emergency care (2012-2016) are based on data from Center for Medicare and Medicaid Services. Estimates for foreign-born share are based on IPUMS 5% 2000 and ACS 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma.

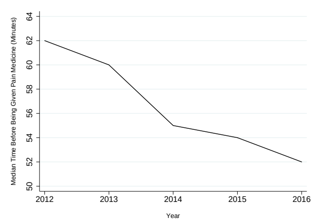
Figure 3.1: National Trends in Emergency Care Department



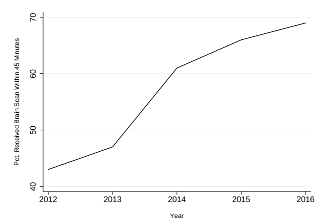
Median Time (Minutes) Before Being Seen by a Healthcare Professional



Median Time (Minutes) Spent in ED After Being Admitted as Inpatient Before Leaving for Inpatient Room



Median Time (Minutes) Before Receiving Pain Medication for Broken Bones



Pct. with Stroke Symptoms Received Brain Scan Results within 45 Minutes of Arrivals

Table 3.2: Effect of Low-skilled Immigration on the Natural Log of Share of Natives Reporting Poor Health

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ LS Immigrant/Population	-24.134	-11.118	10.524	8.608
	(7.908)	(3.721)	(8.088)	(8.343)
	[0.004]	[0.004]	[0.199]	[0.307]
Panel B (2SLS)				
Δ LS Immigrant/Population	-31.738	0.846	0.174	22.906
	(15.660)	(18.965)	(21.405)	(19.975)
	[0.043]	[0.964]	[0.994]	[0.251]
First Stage Coefficient	0.641	0.636	0.633	0.636
	(0.143)	(0.141)	(0.146)	(0.141)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	20.25	20.26	18.86	20.26
Observations	781	816	785	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of share of natives reporting poor health. The number of observations are slightly different in each column because of zero values in the dependent variable, which are being dropped when taking a log. All regressions include controls for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.3: Effect of Low-skilled Immigration on the Natural Log Share of Natives Reporting Work Disability

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ LS Immigrant/Population	-13.820	0.673	-12.675	0.763
	(7.430)	(2.717)	(8.668)	(2.620)
	[0.069]	[0.805]	[0.150]	[0.772]
Panel B (2SLS)				
Δ LS Immigrant/Population	-24.276	12.285	-28.865	12.161
	(12.194)	(9.342)	(15.758)	(8.859)
	[0.046]	[0.189]	[0.067]	[0.170]
First Stage Coefficient	0.636	0.636	0.636	0.636
	(0.141)	(0.141)	(0.141)	(0.141)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	20.26	20.26	20.26	20.26
Observations	816	816	816	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of share of natives reporting work disability. All regressions include controls for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.4: Effect of Low-skilled Immigration on the Natural Log of Share of Natives Reporting Ever Quit a Job Because of Health Reasons

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ LS Immigrant/Population	-28.054	2.812	-26.464	2.901
	(9.505)	(5.376)	(9.526)	(5.189)
	[0.005]	[0.603]	[0.008]	[0.579]
Panel B (2SLS)				
Δ LS Immigrant/Population	-63.723	3.019	-68.345	2.895
	(32.756)	(15.090)	(35.608)	(14.955)
	[0.052]	[0.841]	[0.055]	[0.847]
First Stage Coefficient	0.646	0.636	0.646	0.636
	(0.146)	(0.141)	(0.146)	(0.141)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	19.62	20.26	19.62	20.26
Observations	793	816	793	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of share of natives reporting ever quit a job because of health reasons. The number of observations are slightly different in each column because of zero values in the dependent variable, which are being dropped when taking a log. All regressions include controls for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.5: Effect of High-skilled Immigration on the Natural Log of Share of Natives Reporting Poor Health

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ HS Immigrant/Population	3.849	5.065	13.135	1.361
	(7.848)	(6.777)	(6.068)	(5.373)
	[0.626]	[0.458]	[0.035]	[0.801]
Panel B (2SLS)				
Δ HS Immigrant/Population	7.127	13.552	42.699	-4.473
	(16.779)	(14.550)	(14.981)	(15.104)
	[0.671]	[0.352]	[0.004]	[0.767]
First Stage Coefficient	0.695	0.699	0.700	0.699
	(0.133)	(0.133)	(0.134)	(0.133)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	27.32	27.82	27.45	27.82
Observations	781	816	785	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ HS Immigrant/Population estimates show the effect of high-skilled immigration on the natural log of share of natives reporting poor health. The number of observations are slightly different in each column because of zero values in dependent variable, which are being dropped when taking a log. All regressions include controls for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.6: Effect of High-skilled Immigration on the Natural Log of Share of Natives Reporting Work Disability

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ HS Immigrant/Population	2.590	1.898	-0.552	3.089
	(4.340)	(2.405)	(5.563)	(2.274)
	[0.553]	[0.434]	[0.921]	[0.180]
Panel B (2SLS)				
Δ HS Immigrant/Population	-3.716	-0.655	-13.786	2.321
	(12.093)	(4.310)	(11.038)	(3.907)
	[0.759]	[0.879]	[0.212]	[0.552]
First Stage Coefficient	0.699	0.699	0.699	0.699
	(0.133)	(0.133)	(0.133)	(0.133)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	27.82	27.82	27.82	27.82
Observations	816	816	816	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ HS Immigrant/Population estimates show the effect of high-skilled immigration on the natural log of share of natives reporting work disability. All regressions include controls for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.7: Effect of High-skilled Immigration on the Natural Log of Share of Natives Reporting Ever Quit a Job Because of Health Reasons

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ HS Immigrant/Population	-22.549	2.651	-25.758	3.842
	(13.183)	(4.454)	(12.408)	(4.276)
	[0.093]	[0.554]	[0.043]	[0.373]
Panel B (2SLS)				
Δ HS Immigrant/Population	21.729	0.198	11.000	3.174
	(15.339)	(6.640)	(17.485)	(6.636)
	[0.157]	[0.976]	[0.529]	[0.632]
First Stage Coefficient	0.704	0.699	0.704	0.699
	(0.136)	(0.133)	(0.136)	(0.133)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	26.87	27.82	26.87	27.82
Observations	793	816	793	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ HS Immigrant/Population estimates show the effect of high-skilled immigration on the natural log of share of natives reporting ever quit a job because of health reasons. The number of observations are slightly different in each column because of zero value in dependent variable, which is being dropped when taking a log. All regressions include controls for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Figure 3.2: 1995 Cuban Refugee Inflow and Low-skilled Immigrants Share in Miami

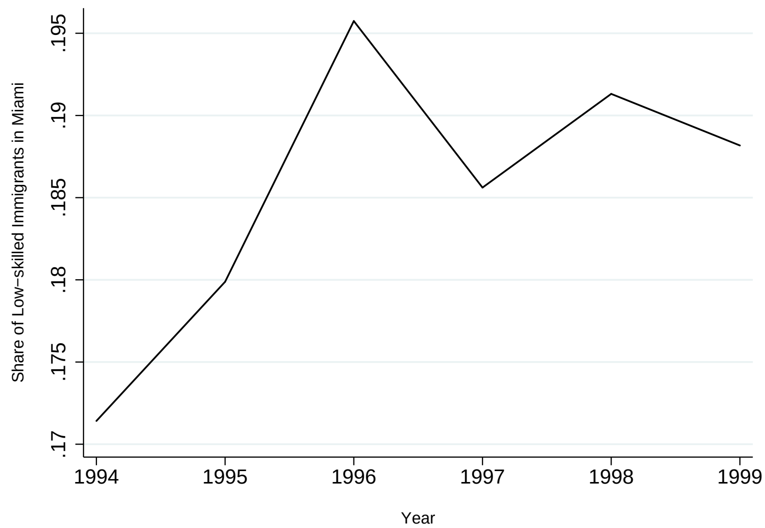


Table 3.8: Cuban Refugee Inflow and Low-skilled Immigrants Share in Miami

Miami x Post 1994	0.015 (0.002) [0.000]
Share of LS Immigrant in 1994 Miami	0.17
Observations	1457

Notes: Estimates are based on IPUMS CPS ASEC 1994-1999. Low-skilled is defined as individuals without a high school diploma. All regressions include controls for demographics and economics conditions as well as metropolitan area and year fixed effects. Observations in the regression analysis are weighted by the metropolitan area population. Heteroskedastic- and cluster-robust standard error at metropolitan area level in the parentheses. p-value in the brackets.

Table 3.9: Evidence from Cuban Refugee Inflow in 1995

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (Dep. Var. : Share of Natives Reporting Work Disability)				
Miami x Post 1994	-0.115	-0.020	0.031	-0.017
	(0.013)	(0.003)	(0.022)	(0.003)
	[0.000]	[0.000]	[0.162]	[0.000]
Share of Natives Reporting Work Disability in 1994	0.289	0.073	0.236	0.059
Observations	1457	1457	1457	1457
Panel B (Dep. Var. : Share of Natives Reporting Ever Quit a Job Because of Health Reasons)				
Miami x Post 1994	-0.015	-0.012	0.024	-0.011
	(0.010)	(0.002)	(0.014)	(0.002)
	[0.137]	[0.000]	[0.078]	[0.000]
Share of Natives Reporting Ever Quit a Job Because of Health Reasons in 1994	0.097	0.030	0.079	0.024
Observations	1457	1457	1457	1457

Notes: Estimates are based on IPUMS CPS ASEC 1994-1999. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. All regressions include controls for demographic and economic conditions as well as metropolitan area and year fixed effects. Observations in the regression analysis are weighted by the metropolitan area population. Heteroskedastic- and cluster-robust standard error at metropolitan area level in the parentheses. *p*-value in the brackets.

Table 3.10: Effect of Immigration on Proxies for Emergency Department Crowding

	Minutes Before Being Seen by Healthcare Professionals	Minutes After Being Admitted as Inpatient Before Leaving for Inpatient Room	Minutes Before Being Given Pain Medication for Broken Bones	Pct. with Stroke Symptoms Received Brain Scan Results within 45 Minutes of Arrivals
Panel A (OLS)				
Δ Immigrant/Population	-1.025	0.517	0.142	1.363
	(2.623)	(0.871)	(1.263)	(2.611)
	[0.698]	[0.555]	[0.911]	[0.604]
Panel B (2SLS)				
Δ Immigrant/Population	-65.611	19.129	6.826	-2.535
	(42.958)	(9.896)	(5.045)	(6.482)
	[0.127]	[0.053]	[0.176]	[0.696]
First Stage Coefficient	0.512	0.498	0.512	0.527
	(0.180)	(0.184)	(0.180)	(0.181)
	[0.005]	[0.008]	[0.005]	[0.004]
Robust F-Stats.	8.06	7.34	8.06	8.44
Observations	202	204	202	201

Notes: Estimates are based on ACS 2012-2016 and CMS 2012-2016. The period of analysis is 2013-2016. The Δ Immigrant/Population estimates show the effect of one percentage point increase in the number of foreign-born relative to the initial population on proxies for emergency department crowding. The number of observations are slightly different in each column because of zero/missing value in dependent variable. All regressions include control for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. *p*-value in the brackets.

3.6 Appendix

Table 3.11: 1970 Immigrant Shares Correlates

	North-western Europe	Eastern Europe	Southern Europe
Share of Blacks in Population	-0.016	-0.021	-0.017
	(0.008)	(0.013)	(0.015)
Share of Married Individuals in Population	-0.180	-0.301	-0.240
	(0.056)	(0.089)	(0.137)
Employment to Population Ratio	0.085	0.058	0.071
	(0.021)	(0.034)	(0.040)
Unemployment Rate	0.261	-0.003	0.047
	(0.051)	(0.067)	(0.085)
Average Age in the State	0.002	0.004	0.004
	(0.001)	(0.001)	(0.001)
Observations	51	51	51

Notes: Estimates are based on IPUMS 1970 Census. Observations in the regression analysis are weighted by the state population. Robust standard error in the parentheses.

Table 3.12: Sensitivity Checks (More Country Groups in Constructing Network Instrument)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (Poor Health Status)				
Δ LS Immigrant/Population	-27.669	0.522	4.652	22.322
	(16.994)	(20.685)	(20.363)	(18.020)
	[0.103]	[0.980]	[0.819]	[0.215]
Panel B (Work Disability)				
Δ LS Immigrant/Population	-22.908	11.964	-26.329	11.862
	(12.009)	(9.405)	(14.480)	(9.016)
	[0.056]	[0.203]	[0.069]	[0.188]
Panel B (Ever Quit Because of Health Reasons)				
Δ LS Immigrant/Population	-70.014	4.466	-73.647	4.364
	(37.581)	(14.893)	(39.616)	(14.565)
	[0.062]	[0.764]	[0.063]	[0.764]

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of share of natives reporting poor health outcomes. All regressions include controls for demographics and economic conditions as well as state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.13: Effect of Low-skilled Immigration on the Natural Log of Share of Natives Reporting Poor Health (Include Demographics and Economics Controls)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ LS Immigrant/Population	-24.035	-11.295	7.875	8.707
	(8.300)	(3.925)	(7.711)	(9.079)
	[0.006]	[0.006]	[0.312]	[0.342]
Panel B (2SLS)				
Δ LS Immigrant/Population	-33.724	6.164	1.720	19.522
	(18.051)	(20.153)	(19.163)	(22.443)
	[0.062]	[0.760]	[0.928]	[0.384]
First Stage Coefficient	0.660	0.653	0.652	0.653
	(0.151)	(0.148)	(0.153)	(0.148)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	19.13	19.44	18.27	19.44
Observations	781	816	785	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of share of natives reporting poor health. The number of observations are slightly different in each column because of zero values in the dependent variable, which are being dropped when taking a log. All regressions include controls for demographics and economic conditions as well as state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.14: Effect of Low-skilled Immigration on the Natural Log of Share of Natives Reporting Work Disability (Include Demographics and Economics Controls)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ LS Immigrant/Population	-13.666	-0.072	-11.668	0.050
	(7.227)	(2.551)	(8.679)	(2.511)
	[0.064]	[0.977]	[0.185]	[0.984]
Panel B (2SLS)				
Δ LS Immigrant/Population	-21.668	8.960	-25.859	9.234
	(12.185)	(7.829)	(16.167)	(7.578)
	[0.075]	[0.252]	[0.110]	[0.223]
First Stage Coefficient	0.653	0.653	0.653	0.653
	(0.148)	(0.148)	(0.148)	(0.148)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	19.44	19.44	19.44	19.44
Observations	816	816	816	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of share of natives reporting work disability. All regressions include controls for demographics and economics conditions as well as state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. *p*-value in the brackets.

Table 3.15: Effect of Low-skilled Immigration on the Natural Log of Share of Natives Reporting Ever Quit a Job Because of Health Reasons (Include Demographics and Economics Control)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ LS Immigrant/Population	-26.848	2.322	-24.508	2.444
	(9.471)	(5.207)	(9.372)	(5.071)
	[0.007]	[0.658]	[0.012]	[0.632]
Panel B (2SLS)				
Δ LS Immigrant/Population	-52.657	3.087	-57.402	3.361
	(26.628)	(15.410)	(30.084)	(15.157)
	[0.048]	[0.841]	[0.056]	[0.825]
First Stage Coefficient	0.669	0.653	0.669	0.653
	(0.151)	(0.148)	(0.151)	(0.148)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	19.72	19.44	19.72	19.44
Observations	793	816	793	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of share of natives reporting ever quit a job because of health reasons. The number of observations are slightly different in each column because of zero values in dependent variable, which are being dropped when taking a log. All regressions include controls for demographics and economics conditions as well as state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.16: Effect of High-skilled Immigration on the Natural Log of Share of Natives Reporting Poor Health (Include Demographics and Economics Control)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ HS Immigrant/Population	4.686	3.373	11.618	1.656
	(7.779)	(6.289)	(6.377)	(5.116)
	[0.550]	[0.594]	[0.074]	[0.748]
Panel B (2SLS)				
Δ HS Immigrant/Population	9.531	5.586	35.129	2.248
	(19.769)	(13.828)	(18.228)	(16.487)
	[0.630]	[0.686]	[0.054]	[0.892]
First Stage Coefficient	0.713	0.713	0.713	0.713
	(0.124)	(0.124)	(0.124)	(0.124)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	32.86	33.11	33.31	33.11
Observations	781	816	785	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ HS Immigrant/Population estimates show the effect of high-skilled immigration on the natural log of share of natives reporting poor health. The number of observations are slightly different in each column because of zero values in dependent variable, which are being dropped when taking a log. All regressions include controls for demographics and economics conditions as well as state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.17: Effect of High-skilled Immigration on the Natural Log of Share of Natives Reporting Work Disability (Include Demographics and Economics Control)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ HS Immigrant/Population	1.397	2.569	-1.147	3.780
	(4.139)	(2.468)	(5.300)	(2.333)
	[0.737]	[0.303]	[0.830]	[0.111]
Panel B (2SLS)				
Δ HS Immigrant/Population	-9.675	3.257	-18.953	5.967
	(15.655)	(4.343)	(13.267)	(4.552)
	[0.537]	[0.453]	[0.153]	[0.190]
First Stage Coefficient	0.713	0.713	0.713	0.713
	(0.124)	(0.124)	(0.124)	(0.124)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	33.11	33.11	33.11	33.11
Observations	816	816	816	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ HS Immigrant/Population estimates show the effect of high-skilled immigration on the natural log of share of natives reporting work disability. All regressions include controls for demographics and economics conditions as well as state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. *p*-value in the brackets.

Table 3.18: Effect of High-skilled Immigration on the Natural Log of Share of Natives Reporting Ever Quit a Job Because of Health Reasons (Include Demographics and Economics Control)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ Immigrant/Population	-22.325	3.026	-24.990	4.236
	(12.192)	(4.303)	(11.553)	(4.150)
	[0.073]	[0.485]	[0.035]	[0.312]
Panel B (2SLS)				
Δ Immigrant/Population	12.789	0.344	2.941	3.054
	(15.592)	(7.416)	(17.679)	(7.799)
	[0.412]	[0.963]	[0.868]	[0.695]
First Stage Coefficient	0.713	0.713	0.713	0.713
	(0.128)	(0.124)	(0.128)	(0.124)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	31.18	33.11	31.18	33.11
Observations	793	816	793	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ HS Immigrant/Population estimates show the effect of high-skilled immigration on the natural log of share of natives reporting ever quit a job because of health reasons. The number of observations are slightly different in each column because of zero values in dependent variable, which are being dropped when taking a log. All regressions include controls for demographics and economics conditions as well as state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. *p*-value in the brackets.

Table 3.19: Effect of Low-skilled Immigration on the Natural Log of Low-skilled Natives Out-migration Rate

	OLS	IV
Δ LS Immigrant/Population	2.940	8.064
	(3.335)	(7.856)
	[0.382]	[0.305]
First Stage Coefficient		0.637
		(0.142)
		[0.000]
Robust F-Stats.		20.23
Observations	816	816

Notes: Estimates are based on ACS 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of low-skilled natives out-migration rate. All regressions include control for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.20: Effect of Low-skilled Immigration on the Natural Log of Relative Tasks (Communication/Manual) Supplied by Natives

	OLS	IV
Δ LS Immigrant/Population	0.436	1.202
	(0.205)	(0.505)
	[0.038]	[0.017]
First Stage Coefficient		0.636
		(0.141)
		[0.000]
Robust F-Stats.		20.26
Observations	816	816

Notes: Estimates are based on IPUMS 5% 2000 Census and ACS 2001-2016. The period of analysis is 2001-2016. The relative task for each occupation is constructed based on Peri and Sparber (2009). Low-skilled is defined as individuals without a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of relative task (communication/manual) supplied by natives. All regressions include control for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. *p*-value in the brackets.

Table 3.21: Effect of Low-skilled Immigration on the Natural Log of Share of Natives Reporting Poor Health (>64 Yrs. Old)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ LS Immigrant/Population	-24.334	-14.955	0.069	-23.085
	(12.061)	(7.935)	(9.497)	(8.810)
	[0.049]	[0.065]	[0.994]	[0.012]
Panel B (2SLS)				
Δ LS Immigrant/Population	-48.097	16.426	-0.026	8.094
	(18.083)	(17.603)	(14.303)	(16.072)
	[0.008]	[0.351]	[0.999]	[0.615]
First Stage Coefficient	0.633	0.637	0.638	0.636
	(0.141)	(0.141)	(0.142)	(0.141)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	20.07	20.27	20.12	20.26
Observations	766	812	776	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on the natural log of share of natives reporting poor health. The number of observations are slightly different in each column because of zero values in dependent variable, which are being dropped when taking a log. All regressions include controls for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.22: Effect of High-skilled Immigration on the Natural Log of Share of Natives Reporting Poor Health (>64 Years Old)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (OLS)				
Δ HS Immigrant/Population	18.933	1.078	4.853	-0.889
	(9.805)	(8.792)	(15.318)	(9.625)
	[0.059]	[0.903]	[0.753]	[0.927]
Panel B (2SLS)				
Δ HS Immigrant/Population	-0.964	-45.905	-24.486	-35.141
	(24.079)	(20.058)	(40.540)	(13.316)
	[0.968]	[0.022]	[0.546]	[0.008]
First Stage Coefficient	0.695	0.698	0.706	0.699
	(0.128)	(0.133)	(0.135)	(0.133)
	[0.000]	[0.000]	[0.000]	[0.000]
Robust F-Stats.	29.53	27.73	27.52	27.82
Observations	766	812	776	816

Notes: Estimates are based on IPUMS 5% 2000 Census, ACS 2001-2016, and CPS ASEC 2000-2016. The period of analysis is 2001-2016. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. The Δ HS Immigrant/Population estimates show the effect of high-skilled immigration on the natural log of share of natives reporting poor health. The number of observations are slightly different in each column because of zero values in dependent variable, which are being dropped when taking a log.. All regressions include control for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. p-value in the brackets.

Table 3.23: Evidence from Cuban Refugee Inflow in 1995 (Using Card's Placebo Cities)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (Dep. Var. : Share of Natives Reporting Work Disability)				
Miami x Post 1994	-0.198	-0.004	-0.007	-0.005
	(0.081)	(0.024)	(0.116)	(0.024)
	[0.029]	[0.864]	[0.956]	[0.824]
Share of Natives Reporting Work Disability in 1994	0.289	0.073	0.236	0.059
Observations	30	30	30	30
Panel B (Dep. Var. : Share of Natives Reporting Ever Quit a Job Because of Health Reasons)				
Miami x Post 1994	-0.012	0.009	0.057	0.008
	(0.032)	(0.017)	(0.037)	(0.017)
	[0.718]	[0.610]	[0.148]	[0.646]
Share of Natives Reporting Ever Quit a Job Because of Health Reasons in 1994	0.097	0.030	0.079	0.024
Observations	30	30	30	30

Notes: Estimates are based on IPUMS CPS ASEC 1994-1999. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. All regressions include controls for demographic and economic conditions as well as metropolitan area and year fixed effects. Observations in the regression analysis are weighted by the metropolitan area population. Robust standard error in the parentheses. *p*-value in the brackets.

Table 3.24: Evidence from Cuban Refugee Inflow in 1995 (Using Borjas's Employment Placebo Cities)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (Dep. Var. : Share of Natives Reporting Work Disability)				
Miami x Post 1994	-0.096	-0.021	0.042	-0.022
	(0.095)	(0.014)	(0.138)	(0.015)
	[0.329]	[0.145]	[0.765]	[0.151]
Share of Natives Reporting Work Disability in 1994	0.289	0.073	0.236	0.059
Observations	30	30	30	30
Panel B (Dep. Var. : Share of Natives Reporting Ever Quit a Job Because of Health Reasons)				
Miami x Post 1994	-0.009	-0.002	0.078	-0.001
	(0.061)	(0.014)	(0.080)	(0.014)
	[0.885]	[0.882]	[0.350]	[0.921]
Share of Natives Reporting Ever Quit a Job Because of Health Reasons in 1994	0.097	0.030	0.079	0.024
Observations	30	30	30	30

Notes: Estimates are based on IPUMS CPS ASEC 1994-1999. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. All regressions include controls for demographics and economics conditions as well as metropolitan area and year fixed effects. Observations in the regression analysis are weighted by the metropolitan area population. Robust standard error in the parentheses. *p*-value in the brackets.

Table 3.25: Evidence from Cuban Refugee Inflow in 1995 (Using Borjas's Low-skill Placebo Cities)

	Men		Women	
	Low-skilled	High-skilled	Low-skilled	High-skilled
Panel A (Dep. Var. : Share of Natives Reporting Work Disability)				
Miami x Post 1994	-0.135	-0.023	0.047	-0.018
	(0.031)	(0.014)	(0.077)	(0.010)
	[0.001]	[0.124]	[0.547]	[0.105]
Share of Natives Reporting Work Disability in 1994	0.289	0.073	0.236	0.059
Observations	30	30	30	30
Panel B (Dep. Var. : Share of Natives Reporting Ever Quit a Job Because of Health Reasons)				
Miami x Post 1994	-0.015	-0.010	0.045	-0.009
	(0.022)	(0.008)	(0.029)	(0.006)
	[0.496]	[0.217]	[0.147]	[0.180]
Share of Natives Reporting Ever Quit a Job Because of Health Reasons in 1994	0.097	0.030	0.079	0.024
Observations	30	30	30	30

Notes: Estimates are based on IPUMS CPS ASEC 1994-1999. Low-skilled is defined as individuals without a high school diploma, while high-skilled is defined as those with at least a high school diploma. All regressions include controls for demographics and economics conditions as well as metropolitan area and year fixed effects. Observations in the regression analysis are weighted by the metropolitan area population. Robust standard error in the parentheses. *p*-value in the brackets.

Table 3.26: Effect of Low-skilled Immigration on Proxies for Emergency Department Crowding

	Minutes Before Being Seen by Healthcare Professionals	Minutes After Being Admitted as Inpatient Before Leaving for Inpatient Room	Minutes Before Being Given Pain Medication for Broken Bones	Pct. with Stroke Symptoms Received Brain Scan Results within 45 Minutes of Arrivals
Panel A (OLS)				
Δ LS Immigrant/Population	-2.794	1.903	-0.567	2.696
	(5.733)	(1.783)	(1.573)	(3.555)
	[0.628]	[0.291]	[0.720]	[0.452]
Panel B (2SLS)				
Δ LS Immigrant/Population	-167.969	52.929	16.714	7.279
	(232.108)	(66.487)	(23.888)	(23.417)
	[0.469]	[0.426]	[0.484]	[0.756]
First Stage Coefficient	0.319	0.311	0.319	0.317
	(0.440)	(0.441)	(0.440)	(0.440)
	[0.469]	[0.481]	[0.469]	[0.473]
Robust F-Stats.	0.53	0.50	0.53	0.52
Observations	202	204	202	201

Notes: Estimates are based on ACS 2012-2016 and CMS 2012-2016. The period of analysis is 2013-2016. The Δ LS Immigrant/Population estimates show the effect of low-skilled immigration on proxies for emergency department crowding. Low-skilled is defined as individuals without a high school diploma. The number of observations are slightly different in each column because of zero/missing value in dependent variable. All regressions include control for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. *p*-value in the brackets.

Table 3.27: Effect of High-skilled Immigration on Proxies for Emergency Department Crowding

	Minutes Before Being Seen by Healthcare Professionals	Minutes After Being Admitted as Inpatient Before Leaving for Inpatient Room	Minutes Before Being Given Pain Medication for Broken Bones	Pct. with Stroke Symptoms Received Brain Scan Results within 45 Minutes of Arrivals
Panel A (OLS)				
Δ HS Immigrant/Population	0.529	-0.625	0.671	0.078
	(2.459)	(1.522)	(1.203)	(2.893)
	[0.830]	[0.683]	[0.579]	[0.978]
Panel B (2SLS)				
Δ HS Immigrant/Population	-42.211	12.331	4.566	-4.491
	(38.182)	(7.133)	(3.702)	(9.885)
	[0.269]	[0.084]	[0.217]	[0.650]
First Stage Coefficient	1.054	1.061	1.054	1.125
	(0.420)	(0.416)	(0.420)	(0.429)
	[0.013]	[0.012]	[0.013]	[0.010]
Robust F-Stats.	6.30	6.49	6.30	6.88
Observations	202	204	202	201

Notes: Estimates are based on ACS 2012-2016 and CMS 2012-2016. The period of analysis is 2013-2016. The Δ HS Immigrant/Population estimates show the effect of high-skilled immigration on proxies for emergency department crowding. High-skilled is defined as those with at least a high school diploma. The number of observations are slightly different in each column because of zero/missing value in dependent variable. All regressions include control for state and year fixed effects. Observations in the regression analysis are weighted by the state population in 2000. Heteroskedastic- and cluster-robust standard error at state level in the parentheses. *p*-value in the brackets.

Chapter 4

Conclusions

This dissertation is an attempt to extend our understanding of how a country may benefit from immigration as well as to examine the potential costs associated with immigration. In the first chapter, "An Inquiry on the Impact of Highly-skilled STEM Immigration on the U.S. Economy," I examine whether foreign STEM workers displace or complement U.S.-born STEM workers and estimate the potential benefit of high-skilled immigration. An important finding obtained through the model is that similarly skilled U.S. and foreign-born STEM workers are imperfect substitutes, implying that it is relatively hard for U.S. firms to fully replace its native STEM workers with their foreign-born counterparts. Furthermore, I estimated that STEM immigration from 2000 to 2015 yields approximately 103 billion USD (1.03% of U.S. GDP in 1999) benefit for U.S.-born workers.

Although immigration has benefits, there may be costs associated with admitting more immigrants into the country. In particular, there are concerns that undocumented immigration may lead to higher crime rates. In the second chapter, "On the Association Between Undocumented Immigration and Crime in the United States," I examine whether this is the case. I started the analysis by examining the institutionalization (incarceration) rate of undocumented immigrants. A higher institutionalization rate among undocumented immigrants would imply that they are indeed more likely to be involved in crimes compared to other U.S. residents. I found that undocumented immigrants are approximately 33% less likely to be institutionalized compared to U.S. natives, despite possessing many characteristics usually associated with crime. Furthermore, I fail to find evidence that undocumented immigrants who have spent more time in the U.S. are more likely to be institutionalized compared to those who have been in the U.S. for a shorter time. Consistent with these findings, I found no evidence that undocumented immigration statistically significantly increased the overall violent and property crime rates across the U.S. states.

The findings in the first chapter suggest that high-skilled immigration is economically beneficial for the country. However, are there any benefits from an inflow of low-skilled migrants? In the final chapter, "Immigration and the Health of United States Natives," I examine the potential benefit of low-skilled immigration on the health of U.S.-born population. The results of the analysis fail to show that the health of U.S. natives is adversely affected by immigration. Instead, the findings suggest that low-skilled immigration improves the health of low-skilled U.S.-born individuals. A one percentage point increase in the number of low-skilled immigrants relative to the initial population of a state is associated with an approximately 31% decrease in the share of low-skilled U.S.-born men reporting poor health. Furthermore, a one percentage point increase in the number of low-skilled immigrants relative to the initial state population is associated with a 24% decrease in the share of low-skilled U.S.-born men reporting work-related disability.

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