The Impact of High-Skilled Immigrants on the Career Outcomes of Natives

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Abstract

The share of college-educated immigrants in the U.S. economy has increased considerably over the last five decades, particularly in science and engineering occupations. In the first chapter of this dissertation, I examine the effects of high-skilled immigrants on natives' post-secondary degree attainment, employment, and earnings. I develop a dynamic discrete choice model of individual choice regarding bachelor's degree major, attainment of advanced degree, and occupation. Unlike earlier studies, I model the determination of earnings in equilibrium as an outcome of a market-clearing process. I estimate the model with the Method of Simulated Moments, using data from the Current Population Survey (1964-2010), the American Community Survey, and the National Survey of College Graduates. I use the estimates to simulate a counterfactual economy. The estimates show that, if the population of high-skilled immigrants remained at its 1960 level, the number of native engineering majors would have been 6.1 percent higher and their employment in engineering jobs would have increased by 8.1 percent; however, their average earnings would have been almost no different in engineering and slightly lower in managerial professions. These findings suggest that 1) the impact of immigration on natives' educational attainment is large, 2) the equilibrium effects offset potential gains in earnings because natives move to fields that are protected from immigration, and 3) natives' earnings in complementary occupations, such as management, are affected adversely by restricted immigration.

In the second chapter, I analyze how visa policy affects the transition of international students studying at U.S. colleges and universities to the U.S. labor market and its potential consequences on the labor market outcomes of native counterparts. Retention of these students in the United States may contribute to innovation and growth, but may also adversely impact native employment and earnings. Optional Practical Training (OPT) permits international students to work in the United States for a limited period after graduation without holding a formal work visa. The increase in the allowable length of stay for students in science, technology, engineering, and mathematics (STEM) via the OPT program in 2008 provides an opportunity to assess how visa terms affect the supply of high-skilled labor to the U.S. economy. My estimates show that extended visa terms increase the initial entry of international students into the U.S. labor market and lengthen the duration of employment, especially for master's-level students. I also find that the increase in the labor supply of foreign workers reduces native employment and earnings for recent master's level STEM graduates.

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Contents

Chapter 1

The Effects of High-Skilled Immigrants on Natives' Degree Attainment and Occupational Choices: An Analysis with Labor Market Equilibrium

I. Introduction

The share of immigrants among college-educated workers has increased considerably over the last five decades, particularly in science and engineering occupations. As of 2010, immigrants accounted for about one quarter of all engineers and about half of those with advanced degrees in the U.S. workforce.[1] Although foreign scientists and engineers might boost innovation and the growth rate of the U.S. economy, increases in their supply might concurrently harm labor market opportunities and discourage native students from pursuing science and engineering degrees. This possibility of crowding out natives from science and engineering raises a concern about maintaining U.S. leadership in innovation, especially if foreign scientists and engineers leave the U.S. workforce as competition among nations to attract these talented workers grows (National Academy of Science 2005). In this study, I analyze to what extent high-skilled immigrants affect natives' post-secondary degree attainment and labor market outcomes. I build and estimate a dynamic discrete choice model where earnings are determined in equilibrium. Taking the flow of immigrants as given, the unit price of each type of high-skilled worker is determined as an outcome of a market-clearing process, and earnings of each person are specified as a function of the unit skill prices. I use the estimates of the model to simulate the effects of high-skilled immigrants on natives' choice of college major, attainment of advanced degrees, occupation choices, and earnings.

Unlike the earlier literature, I estimate the effects of high-skilled immigrants on college-educated natives' education and labor market outcomes jointly and model the

[1] The share of immigrants within the college-educated workforce has increased from about 7.1% in 1950 to 17% in 2010 (author's tabulations from the decennial U.S. Census 1950-2000 and the American Community Survey 2009-2011). See Section II for a detailed discussion of the patterns in immigration to the United States.

determination of earnings as an outcome of a market-clearing process.[2] This approach allows me to deal with two limitations in the current literature. First, I can quantify the effects of immigration due to the dynamic-decision making of native students. Since immigrant entry alters earning trajectories in each field, native students of each birth cohort experience different values of expected lifetime utility from choosing each bachelor's degree alternative. The dynamic discrete choice model allows me to capture how bachelor's degree choices of natives respond to immigration. Second, I can quantify the effects of immigration on earnings after incorporating adjustments in natives' education and occupational choices. If the entry of high-skilled immigrants were restricted, more natives would have gotten degrees in fields that are protected from immigration and worked in associated occupations. Such adjustments in natives' behavior would have increased the counterfactual labor supply in those occupations, thereby mitigating the potential increases in earnings from restricting immigration.

The structure of the model is similar to earlier studies of labor market equilibrium that ignore immigration (e.g., Heckman et al. 1998, Lee 2005, and Lee and Wolpin 2006, 2010).[3] I focus on the labor supply of high-skilled native and immigrant workers (those with college degrees) by modeling their education and occupational choices as a dynamic discrete choice problem. In the model, each individual chooses a bachelor's major that maximizes her expected lifetime utility at the beginning of her career at age 20. Once the individual graduates from college at age 22, she then makes an optimal career choice among the alternatives of advanced degrees and occupations each year until age 65. I

[2] One strand of literature explores the relationship between the supply of high-skilled foreign workers and natives' employment and earnings across labor markets that are defined by geography (e.g., Kerr and Lincoln 2010, Kerr et al. 2015, Peri et al. 2015) or by field of study (e.g., Borjas 2009, Borjas and Doran 2012, Lan 2013). On the other hand, some researchers assess whether the prevalence of foreign workers in a particular area (or foreign students in a particular school) affects natives' educational attainment in the same area (e.g., Borjas 2007, Orrenius and Zavodny 2013, Jackson 2015, Shih 2015, Bound et al. 2016). To my knowledge, only two studies estimate the effects of immigration on the education and labor supply behavior jointly in the context of immigration into the United States, but I consider a wider set of education and occupation alternatives. In particular, Bound et al. (2015) focus on computer sciences and estimate the effects on native's likelihood to major and work in computer sciences and their earnings relative to other science and engineering workers. Llull (2016) analyzes the effects of all immigrants, including non-college graduates, specifying the educational attainment with schooling years (rather than post-secondary degrees) and occupations as blue-collar and white-collar. See Section II for a detailed review of the literature.

[3] Heckman et al. (1998) develop an equilibrium model of labor earnings and skill formation with overlapping generations to analyze the rising wage inequality in the Unites States. Lee and Wolpin (2006) estimate a similar model by introducing unobserved heterogeneity to examine the rising share of service-sector workers over the last five decades. My model differs from the earlier studies by separating the labor supply of immigrants from natives and modeling educational attainment with degree types, instead of schooling years.

aggregate occupations and fields of study at each level of post-secondary degree (bachelor's, master's, and doctorate/professional degrees) into four career paths: i) business, ii) engineering, iii) science, and iv) "other" fields.

Depending on the choice of occupation and degree attainment, each individual accumulates occupation-specific skills. The aggregation of the skill units of those who choose to work in each occupation determines the total supply of the high-skilled labor of the relevant type. Capital, low-skilled workers, and high-skilled workers of four types produce a final product in a one-sector economy. The production technology is assumed to follow a nested constant-elasticity-of- substitution production function, and it determines the aggregate demand of each factor of production. Capital and low-skilled workers are assumed to have a perfectly elastic supply. The market-clearing process determines the unit price of each type of high-skilled labor in equilibrium. The earnings of each college graduate are determined as a function of the unit skill prices and her accumulated skills in each occupation.

I estimate the model using the Method of Simulated Moments. I use data from several sources, including the Current Population Survey (1964-2010), the decennial U.S. Census (1960-2000), the American Community Survey (2009-2011), and the National Survey of College Graduates (1993, 2003, and 2010). I minimize the distance between the moments of data and simulated counterparts from the model. I use aggregate moments describing college graduates' characteristics of employment and earnings in each occupation, transitions between career paths, and post-secondary degree attainment in the estimation.

Depending on the population and composition of college-educated immigrants entering the economy over time, immigration increases the supply of high-skilled labor of each type. As a result, the unit price of each skill type changes in equilibrium. These changes make natives adjust their labor supply and degree attainment behavior. Thus, to quantify the effects of immigration on natives' behavior, I simulate a counterfactual economy by restricting the population of high-skilled immigrants to its 1960 level.

This simulation exercise suggests three main outcomes. First, the impact of high-skilled immigrants on natives' degree attainment and occupational choice would have been large. The results show that the number of native engineering and science majors would have increased by 6.1% and 4.4%, respectively. Similarly, natives' advanced degree attainment in engineering and science at the master's and doctorate/professional levels would have grown in the range of 5.0% to 8.8%. Consistent with the compositional changes in natives' degree attainment, their employment would have grown by 8.1% in engineering and by 6.8% in science jobs (including the medical professions). These results suggest that it is important to consider education choices and labor market outcomes jointly in an analysis of immigration to understand the full impact of immigrants.

Second, the equilibrium mechanism mostly offsets potential earnings gains that one would have expected in science and engineering occupations if immigration got restricted. The results show that the average earnings of natives would have increased by 0.05% in engineering and by 0.51% in science jobs if the immigrant population were restricted to its 1960 level. The following equilibrium mechanism explains the rationale behind this finding. The restriction of immigration decreases total supply of labor, holding natives' labor supply and education behavior constant. The drop in the supply of skills is expected to increase marginal productivity, thereby increasing wages in engineering and science jobs. In response, more natives pursue degrees and work in these fields. The increase in the supply of skills due to adjustments in natives' behavior pushes the unit skill prices back to a level that is similar to the one observed in the baseline economy. To quantify the role of this mechanism, I simulate the model as follows: reducing the immigrant population but keeping natives' education and occupational choice constant at the levels observed in the baseline economy. In this case, I find that average earnings would have increased by 11.1% in engineering and by 9.1% in science jobs. This finding suggests that the adverse effect of immigration on earnings would have been overestimated if the mitigating role of natives' labor supply adjustments was ignored, as emphasized by Llull (2016) in the context of the immigration of low-skilled workers.

Third, natives' earnings in occupations other than science and engineering would have been affected adversely if the immigration population remained at its 1960 level. The estimates show that earnings would have decreased by 0.18% for native managers and by 0.14% for native "other" professionals. This finding suggests that different types of high-skilled workers are complementary to each other in the production process. As the restriction of high-skilled immigrants reduces the number of engineers and scientists in the overall economy, workers in other occupations become less productive. The previous literature also finds that natives in other occupations, such as management, benefit from immigration into science and engineering fields because they can specialize in complementary jobs by using their comparative advantage in communication and language skills (e.g., Peri and Sparber 2011, Hunt 2012).

The next section provides a brief overview of the patterns in high-skilled immigration into the United States and discusses the previous literature. Section III and IV describe the model and the model solution. Section V introduces the data and discusses estimation and identification. Section VI provides the parameter estimates and model fit. Section VII presents the effects of immigration. Section VIII concludes.

II. Research Background

A. College-Educated Workers and Immigration

The population of college-educated people in the U.S. workforce increased from about 3 million in 1950 to 35.2 million in 2010 as their share grew from 8.4% to 35.4% (see Table 1). The composition of workers across the countries of origin suggests two distinct eras where native- and foreign-born workers play different roles. Natives were the driving force of almost all of the observed expansion in the college-educated workforce from 1950 to 1980.[4] Then, immigrants became an important source, as they made up 29% of those entering into the workforce over the last two decades. As a result, the percentage of college-educated workers who are immigrants increased from 9.9% in 1990 to 17% by 2010. Meanwhile, immigrants' occupational concentration and post-secondary degree attainment have differed noticeably from those of natives. Immigrants have been more likely to work in science and engineering occupations and hold advanced degrees. For instance, immigrants constituted 29.2% of all engineers and 43.6% of those with advanced degrees in the U.S. workforce as of 2010.

Table 1: Share of Immigrants in the U.S. Workforce

Panel A: The Population of Full-Year Full-Time workers (in millions)

	1950	1960	1970	1980	1990	2000	2010
Native							
Less than College-Educated	29.1	35.4	41.4	44.3	52.2	56.9	52.3
Only Bachelor's degrees	1.7	3.0	4.6	8.0	12.2	16.0	18.4
Advanced degrees	1.1	1.3	2.2	4.5	7.0	9.0	10.8
Immigrant							
Less than College-Educated	3.3	2.6	2.5	3.3	5.5	9.1	12.1
Only Bachelor's degrees	0.1	0.2	0.2	0.6	1.2	2.2	3.4
Advanced degrees	0.1	0.1	0.2	0.5	0.9	1.7	2.6

Panel B: Percentage of Immigrants

	1950	1960	1970	1980	1990	2000	2010
By education							
Less than College-Educated	10.2	6.8	5.6	6.9	9.6	13.8	18.7
College-Educated	7.1	5.9	6.2	7.8	9.9	13.6	17.0
Only Bachelor's degrees	6.7	4.8	4.8	6.6	8.9	12.1	15.4
Advanced degrees	7.7	8.5	8.9	9.8	11.6	16.0	19.5
By occupation, College-Educated							
Management	6.9	4.7	4.6	6.1	8.3	11.2	14.5
Engineering	7.7	7.3	9.4	12.2	15.4	23.3	29.2
Health-related	9.4	9.7	11.5	14.4	14.4	18.7	22.1
Other Occupations	6.5	5.6	5.6	7.0	9.2	12.0	15.0
By Occupation, Advanced degrees							
Management	7.7	6.2	6.5	7.2	9.6	13.0	17.2
Engineering	8.2	13.2	15.7	19.3	24.6	35.4	43.6
Health-related	8.6	10.9	14.2	16.5	15.6	20.1	23.3
Other Occupations	7.2	8.0	7.3	8.0	9.5	12.2	14.0

Sources: 1950-2000 Census, 2009-11 ACS.

Note: Figures in Panel A indicate the total number of working people (i.e., employed at least 1,400 hours per year) by education and country of origin. Figures in Panel B indicate the percentage of immigrants in the labor market for the demographic group of interests.

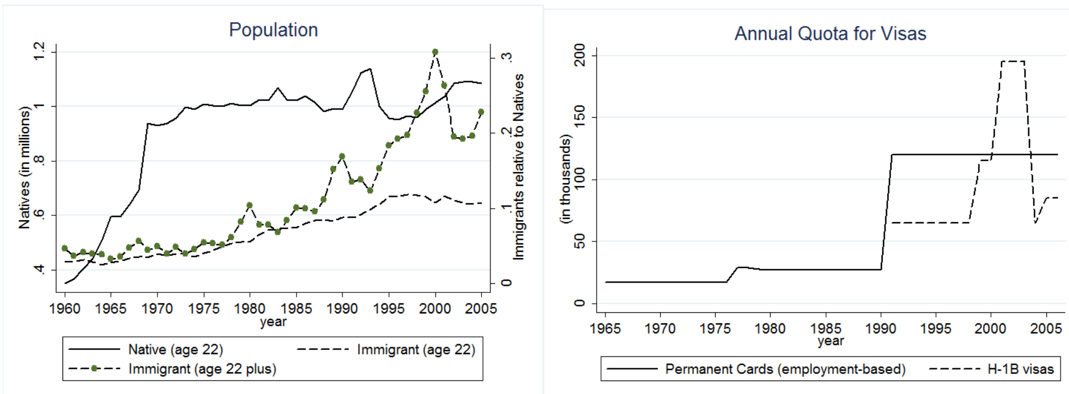
4 The expansion in cohort sizes (the Baby Boom generation), generous federal aid for veterans after the World War II, and college deferments to avoid military service in Vietnam might be important factors in this expansion.

In the left panel of Figure 1, the population of entrants into the college-educated U.S. workforce is displayed for three demographic groups of workers: 1) recent native college graduates, 2) recent immigrant college graduates who grew up and attended college in the United States, and 3) immigrants who arrived in the United States at an age older than 22 with a bachelor's degree obtained abroad.[5] Relative to the population of cohorts of native entrants, the population of immigrants graduating from college in the United States and the population of immigrants arriving at older ages with foreign degrees have both grown over time. However, the population of the latter surpassed the former group of immigrants over the last two decades, especially around the year 2000.

U.S. visa policy was an important factor in explaining the observed pattern of immigration. In particular, the 1990 Immigration Act increased the number of permanent visas available for college-educated immigrants with offers of employment, as displayed in the right panel of Figure 1. The same act also redesigned the H-1B temporary visa program such that it became an important entry channel for high-skilled immigrants (Bound et al. 2014). Consistent with these changes, the presence of immigrants in the U.S. workforce was considerably higher over the last two decades than during previous periods. Moreover, the quotas of H-1B visas and employment-based visas were exhausted almost every year since the act was passed, even during the 1999-2003 period, when the number of H-1B visas was temporarily increased by Congress. In sum, the correlation between the size of immigrant flows and the quota for immigration visas over the last five decades was 0.879.

[5] Because the American Community Survey does not provide the graduation year of bachelor's degree holders, I show the population of college graduates from the native cohort who were 22 years old when the immigrants arrived.

Figure 1: Flows of College-Educated People and Immigrant Visas



Source: ACS 2009-2011 for the left panel and author's tabulations from the U.S. Citizenship and Immigration Services' website for the right panel.

Note: The figure on the left displays the flows of people into the college-educated U.S. workforce for three demographic groups: recent native college graduates (labeled as "Native (Age 22)"), recent immigrant college graduates who grew up and attended college in the United States (labeled as "Immigrant (Age 22)"), and immigrants who arrived in the United States at an age older than 22 with a bachelor's degree obtained abroad (labeled as "Immigrants (Age 22 plus)"). The populations are calculated as the sum of the sample weights for people in the demographic groups of interest. The size of immigrant flows is displayed relative to the population of native cohorts. Because the ACS does not provide the information of when and where the bachelor's degree was obtained, I assume that people graduate from college at age 22 and that immigrants arriving older than that age hold degrees from foreign universities. The figure on the right displays the annual quota for the employment-based permanent visas and the H-1B visas.

In addition to visa policy, labor demand conditions in the U.S. labor market have been likely to affect the characteristics of immigration, including the size of immigrant flows.[6] For instance, the invention of microprocessors in the late 1970s and Internet technology in the late 1990s increased the demand for computer scientists. U.S. firms might have preferred to hire foreign computer scientists in these periods, especially in the short-run, because the training of U.S. students required a lengthy professional education (Bound et al. 2013). A relationship between labor demand conditions and characteristics of immigrants raises some concerns about identification, as discussed in Section V. To illustrate the extent that labor demand shocks change the composition of immigration,

[6] It is also likely that policy makers respond to changing labor demand conditions by revising U.S. visa policy. For instance, policy makers might have intended to meet the demand for computer scientists during the IT boom of the late 1990s by increasing the number of H-1B visas from 1999 to 2003. However, the fact that 2001 recession impacted the IT industry implies potential policy lags. On the other hand, the 1990 Immigration Act was passed as comprehensive immigration reform, similarly expanding family-related permanent visas.

Table 2 shows the bachelor's degree attainment of immigrants in each one of the aggregate fields (business, engineering, science, and other) by distinguishing immigrants according to their year of arrival. The proportion of immigrant entrants with an engineering degree (including the computer sciences) was only slightly higher in the 1990s despite the positive demand conditions in computer sciences during that decade. However, immigrants were noticeably more likely to hold engineering degrees than natives, regardless of the year in which they arrived in the United States. The possibility that technical skills might be more portable from the country of origin than other types of skills might explain the prevalence of immigrants from every arrival period in engineering, given the large wage premium for immigrants in the U.S. labor market for all professions (Clemens 2013).

Table 2: Characteristics of College-Educated People

			Distinguished by Arrival Period of Immigrants				
	Natives	Immigrants	2001-2010	1991-2000	1981-1990	1971-1980	1961-1970
Bachelor's Degrees							
% Management	21.9	22.3	24.5	21.5	23.5	23.1	21.7
% Engineering	13.6	30.6	35.0	36.8	30.6	29.0	25.4
% Science	12.4	16.5	18.8	15.3	15.8	17.8	17.4
% Other	52.1	30.6	21.7	26.4	30.1	30.1	35.5
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Country of Origin							
% Western Europe	-	18.2	13.1	14.6	12.3	13.7	22.7
% Former Soviet	-	5.9	6.3	9.5	5.4	3.3	2.2
% China	-	8.5	7.0	9.9	12.2	6.8	6.5
% India	-	13.0	23.9	18.3	11.2	10.4	8.0
% Rest of Asia	-	30.8	29.8	24.3	35.8	43.1	29.2
% Rest of the World	-	23.6	19.8	23.4	23.2	22.7	31.3
Total	-	100.0	100.0	100.0	100.0	100.0	100.0

Source: National Survey of College Graduates 1993, 2003, and 2010.

Note: The table shows the distribution of the bachelor's degree attainment of immigrants and natives in each one of the fields (business, engineering, science, and other) as well as the distribution of the country of origins of immigrants. Each number presents the percentage of people with the characteristic of interest in each demographic group. The first two columns display the statistics for all natives and immigrants who were aged between 26 and 65 when the survey was conducted. The following columns display the statistics for immigrants by distinguishing them according to their year of arrival in the United States.

The distribution of immigrants across countries of origin, as presented at the bottom panel in Table 2, also provides some insights into determinants of immigration. The percentage of immigrants from developing countries increased over time, especially in the last two decades. For instance, Indians made up 23.9% of all immigrants arriving in the last decade, whereas they comprised less than 10% of those arriving before the 1990s. This shift might have resulted from the increase in the quantity and quality of college graduates in major countries of origin (in particular, China and India) as a result of improvements in their higher education systems (Freeman 2006). Especially over the last two decades, more people from these countries became qualified to work in the U.S. labor market where they had a chance to earn considerably higher wages than they could have earned in their countries of origin (Clemens 2013, Peri 2009). Similarly, more students from these countries began pursuing graduate degrees in U.S. colleges and universities, which served as an important gateway to the U.S. labor force after graduation (Bound et al. 2014). Moreover, the collapse of the Soviet Union and the establishment of diplomatic relations with China increased the migration of high-skilled workers from former Soviet countries during the 1990s and from China after the late 1970s. In particular, immigrants from former Soviet countries made up 9.5% of immigrants arriving in the 1990s, and those from China made up 12.2% of immigrants arriving in the 1980s, while they represented, respectively, only 2.2% and 6.5% of those arriving during the 1960s.

In sum, the presence of immigrants among college-educated workers increased substantially, particularly over the last two decades, and immigrants from every arrival year were more likely to work in engineering compared to natives. U.S. visa policy with its binding quotas for immigration visas, the expansion of the pool of college-educated workers in major source countries, and some international diplomatic shocks, such as the collapse of the Soviet Union, seemed to be the major determinants of the migration of high-skilled workers to the United States. Meanwhile, labor demand shocks changed the skill composition of immigrants slightly, at least across the four categories of occupations studied in this paper. In next section, I discuss the literature regarding the effects of high-skilled immigration.

B. The Literature on the Effects of High-Skilled Immigrants

An increase in the supply of workers, such as the one driven by immigration, is expected to put downward pressure on earnings and employment of competing workers with the magnitude of the decrease depending on the elasticity of labor demand. However, especially in the labor market for high-skilled workers, an increase in labor supply might generate negligible or even positive effects on labor market outcomes. In particular, the contribution of high-skilled workers to the total factor productivity and a highly inelastic labor-demand structure due to agglomeration effects and offshoring (Feenstra 2009) might diminish the potential decrease on earnings and employment.

A growing body of the literature empirically assesses the effects of college-educated immigrants on natives' labor market outcomes. (See Kerr 2013 for a survey article of this literature.) Some researchers define labor markets by geography (e.g., state or city) and explore the link between the level of high-skill immigration and natives' labor market outcomes in each area (e.g., Kerr and Lincoln 2010, Kerr et al. 2015, Peri et al. 2015). Because the immigrant population might be correlated with unobserved labor demand conditions in each market, an instrumental variable methodology is used to address the endogeneity issue. In particular, these papers rely the interaction between variation in the national-level number of H-1B visas and the initial dependency of each area to foreign employment as an instrument. They find that high-skilled immigrants have negligible effects on natives' earnings and employment.

On the other hand, some researchers define labor markets at the national level by differentiating workers in terms of their specialization, such as the field of the highest post-secondary degree (e.g., Borjas 2009, Borjas and Doran 2012, Lan 2013, Bound et al. 2015). Unlike the first set of papers, they find some adverse effects on natives' earnings and employment, mostly for those with graduate degrees. For instance, Borjas and Doran (2012) find that the influx of foreign doctorate-level mathematicians from former Soviet countries crowds out native mathematicians from studying topics similar to immigrants. Lastly, unlike the rest of the literature, Bound et al. (2015) explicitly model the education and labor supply decision of natives for the industry of information technology. They find that the restriction of immigration to its 1994 level would increase the natives' degree attainment and employment in computer sciences. (In Section VII, I compare their results with the estimates of my paper.)

Some researchers explore to what extent foreign scientists and engineers might change natives' occupation choices. In particular, Peri and Sparber (2011) find that native workers move into managerial occupations during the years when the U.S. economy experiences a large influx of foreign scientists and engineers. They interpret this finding to mean that natives prefer to specialize in occupations requiring interactive and communication skills after the entry of immigrants specializing in quantitative skills. Similarly, Hunt (2012) shows that native engineering degree holders earn more than immigrants because the successful ones are promoted to managerial occupations that require better English speaking skills.

In related literature, some researchers explore how immigration affects innovation and productivity in the U.S economy. Without finding any evidence of crowding out in natives' patenting and publishing activities, this literature shows that immigrants are more prone to patent (Hunt and Gauthier-Loiselle 2010), increase the patenting activity of U.S. firms (Kerr and Lincoln 2010, Moser et al. 2014), boost both publishing and patenting activity in U.S. universities and colleges (Chellaraj et al. 2008, Stephan 2010, Stuen et al. 2012), and contribute to the growth of total factor productivity in the U.S. economy (Peri 2012, Peri et al. 2015).

Although a large volume of literature discusses the effects of high-skilled immigration on the U.S. labor market and U.S. innovation, only a few papers focus on the effects of immigration on natives' educational attainment. Most of them find no evidence of crowding out in natives' college enrollment in response to state- or university-level increases in the number of foreign college students (Jackson 2015, Shih 2015, Bound et al. 2016). Only Borjas (2007) presents some adverse effects, but he finds them only for the graduate school attendance of white males. To my knowledge, Orrenius and Zavodny (2013) is the only study exploring the impact of immigrants on the college major choice of natives. Relying on geographical-level variation, they find that increases in the share of immigrants in natives' age cohort reduce the likelihood of native female students majoring in science and engineering fields but not the likelihood of native males.

I contribute to this literature by estimating the effects of immigrants on natives' education and labor market outcomes jointly. In a life-cycle model, forward-looking native students might pursue a different educational path, rather than majoring in science and engineering fields, if they perceive that earnings will be lower in science and engineering jobs due to immigration. The model estimated in this paper captures such a dynamic link between natives' education choices and the immigrants' effects on the expected earnings. In contrast, earlier studies focus on the relationship between natives' education choices in a university (or state) and the number of foreign peers in the same university (state). This approach is more likely to capture crowding out because of potential competition between native and immigrant students for limited resources in universities (or states).

Furthermore, I estimate the effects of immigration on earnings within an equilibrium framework. In other words, I allow adjustments in natives' degree attainment and labor supply behavior in response to changes in the immigrant population, and I then consider the effect of these adjustments on the equilibrium level of skill prices. As discussed in Section VII, the estimated effects on earnings would decline substantially after considering the role of natives' labor supply adjustments in the counterfactual equilibrium.

C. The Literature on the Choice of College Majors

This study also relates to the literature estimating the effects of college majors on earnings. The possibility of self-selection into majors complicates this estimation problem. For example, if students with high aptitude in a certain occupation obtain a bachelor's degree in a related field, a positive correlation between earnings and degree attainment might occur either because of the effect of the degree on human capital or because of the unobserved ability of degree holders. Some researchers attempt to separate the effects of these two factors by including control variables of ability, such as test scores, in the estimation equation of earnings (e.g., James et al. 1989, Hamermesh and Donald 2008, Webber 2014). They find that engineering and science majors increase earnings the most, while business majors increase them the next highest. Berger (1988) finds the same pattern across majors by relying on a control function approach, in which he estimates the probability of choosing each college major with a multinomial logit model.

On the other hand, some researchers model the major choice process as a dynamic discrete choice problem (e.g., Arcidiacono 2004, Beffy et al. 2012, Kinsler and Pavan 2015, Gemici and Wiswall 2014). They find the same ordering of the effects across majors with the highest impact on earnings estimated for engineering and science majors. But the estimates of these structural papers are usually lower than those of the reduced-form literature. (See Table 8 in Altonji et al. 2015 for a comparison of estimates in the literature.) Moreover, the structural papers point out a significant role of unobserved heterogeneity in individuals' preferences for studying each major and their ability in the labor market. I also find that unobserved heterogeneity is an important factor in the choice of post-secondary degrees as discussed in Section VI.

A related strand of the literature explores whether students' choice of college major responds to variation in potential earnings.[7] In line with a life-cycle model of human capital investment, Berger (1988) and Montmarquette et al. (2002) show that the expected lifetime earnings are important determinants of the choice of college majors. Relying on the variation in monetary payoffs across majors over time, Long et al. (2015) find that students' choices respond to earnings in related occupations. The early research in the context of engineering fields shows a similar positive correlation between the

[7] A large body of literature focuses on other aspects of the college major choice. Using subjective expectations data, Zafar (2012, 2013) examines the role of parents in the students' choice of major. Arcidiacono et al. (2014), Stinebrickner and Stinebrickner (2014), and Wiswall and Zafar (2015) study the role of a priori expectations and learning. Turner and Bowen (1999), Gemici and Wiswall (2014), and Bronson (2015) explore the role of gender-specific preferences in choosing college majors. Because of data limitations, I include only gender among these factors to explain the major choice in this study, as discussed in more detail in Section III.

major choice and earnings with the data before 1990 (Freeman 1976, Ryoo and Rosen 2004). This literature shows that students' enrollment in engineering programs increases with positive labor demand shocks, which are instrumented by research and development expenditures. Building upon this finding, my research examines the responsiveness of native students' choice of college major to changes in earnings induced by immigration. Unlike the earlier literature, I differentiate the effect of each bachelor's degree across occupations. Furthermore, I distinguish the effect of each advanced degree from the effect of the bachelors' degrees. As discussed later, I find that the effect of advanced degrees is large and varies widely by the field of study, which suggests the importance of considering advanced degrees in a study of college major choice.

III. Model

I develop a model for a one-sector economy in which homogeneous capital, low-skilled workers, and high-skilled workers of four different types produce a final product. I focus on the labor supply of high-skilled workers by modeling the post-secondary degree attainment and occupation decisions of those with college degrees as a dynamic discrete choice problem.[8]

A period in the model is one year. The sequence of events is as follows. At the beginning of each period, a new sophomore class enters the economy, and each member chooses his bachelor's major, while each of the existing college graduates, who are aged from 22 to 65, makes his career choice. The alternatives are working in a particular occupation, attending graduate school to study a specific advanced degree, or staying at home. At the end of the period, those aged 65 leave the economy, and freshly minted college graduates at age 22 enter the labor force.[9] Meanwhile, immigrants join the economy upon arrival in the country. After their entry, each makes his career choice

[8] I do not model the behavior of the non-college graduates, so I am unable to analyze the impact of immigration on natives' decisions regarding college attendance. Jackson (2014) finds that state-level increases in the number of college-educated immigrants do not lower native enrollment rates. Bound et al. (2015) find a similar result with the university-level analysis for native enrollment in the bachelor's level programs. On the other hand, literature exploring the impact of immigration on the other levels of education finds displacement effects for some but not all natives (e.g., Betts and Fairlie 2003, Borjas 2007, Hunt 2012, Shih 2015).

[9] I do not model students' decisions to drop out of college because the data provide statistics only for completed degrees.

among the alternatives of occupations and post-secondary degrees. I assume that the size and the initial skill endowment of the immigrant cohorts are exogenous to natives' career choices.[10]

Each agent in the model makes an optimal career decision by maximizing expected lifetime utility. Depending on the choice of occupation and degree attainment, each individual accumulates occupation-specific skills. The aggregation of the skill units of those who choose to work determines the total amount of skills in the overall economy. The market-clearing process determines the unit price of each type of high-skilled labor.

The rest of this section describes the model in more detail. Section A formalizes the agents' maximization problem and defines the choice set. Section B discusses the specification of the flow utility for each available choice. Section C describes the aggregate production function. Section D defines the equilibrium.

A. The Maximization Problem

The agents in the model differ by gender and their unobserved heterogeneity type that governs their preference for schooling and ability in the labor market. Assume that individuals are divided into separate groups, where each group includes all individuals of the same gender and type. Let i index individuals in the group of gender g and type k. Describing choices requires two indices. Let j index the alternative (bachelor's degree, master's degree, doctoral/professional degree, working, and staying at home) and f index the field (business, engineering, science, and other areas) of the choices. Each choice is defined as a combination of alternative j and field f. The set of feasible choices of each individual depends on his current degree endowment, as discussed in more detail below. Let $\Psi(\Omega_{igka})$ denote the set of feasible choices of individual i of gender g and type k

[10] As I discuss in Section II, the migration of highly skilled foreign workers to the United States could be determined by factors independent of natives' education and employment behavior. These factors could include improvements to the higher education system in their countries of origin, international diplomatic shocks such as the collapse of the Soviet Union, and U.S. visa policy. Endogenizing the migration decision would require information on immigrants' motives to migrate, which is not available. Some notable papers take immigration as exogenous as well (e.g., Borjas 2003, Llull 2016). On the other hand, some researchers rely on the variation in the number of available H-1B visas (e.g., Kerr and Lincoln 2010, Kerr et al. 2014, Peri et al. 2014) as an exogenous determinant of immigration in a reduced-form set-up with the instrumental variable method. To my knowledge, Bound et al. (2015) is the only exception, modeling the hiring process of foreign workers in the context of the IT industry. See Part B of Section II for a detailed review of this literature.

with the vector Ω_{igka} indicating his degree endowment at age a. Given the feasible choices, each individual makes an optimal decision that maximizes the expected discounted present value of his lifetime utility. For individual igk (i.e., individual i of gender g and type k) at age a, this optimization problem can be formalized as

$$(1) \qquad \max_{d_{igka}^{j,f} \in \Psi(\Omega_{igka})} E\left[\sum_{z=a}^{65} \delta^{z-a} U_{igkz}\right]$$

where δ denotes the discount factor, U_{igkz} the period utility at age z, and $d_{igka}^{j,f}$ a binary variable that is equal to 1 iff alternative j in field f is chosen at age a. The period utility is

$$(2) \qquad U_{igka} = \sum_{d_{igka}^{j,f} \in \Psi(\Omega_{igka})} u_{igka}^{j,f} d_{igka}^{j,f}$$

where $u_{\mathrm{igk}a}^{j,f}$ is the choice-specific period utility associated with choosing alternative j in field f at age a.

Choice Set. At the beginning of his career at age 20, each student chooses a bachelor's degree ($j = B$) in one of the following four fields: i) business $(f = B)$, ii) engineering $(f = E)$, iii) science $(f = S)$, and iv) other areas $(f = O)$. Once the individual graduates from college at age 22, he then makes his career decisions regarding his occupation and the attainment of advanced degrees. The set of feasible choices available to an individual at each age varies with his current degree endowment. If he has only a bachelor's degree, then the choice set consists of the following 13 mutually exclusive alternatives: obtain a master's degree ($j = M$) in one of the four fields or a doctorate/professional degree ($j = D$) in one of the four fields, work ($j = W$) in one of the four occupations, or stay at home ($j = H$). The choice set gets smaller if he holds an advanced degree because each agent can have at most one degree at each level of education by assumption. So, an individual with a master's degree has nine choices instead of 13 because obtaining another master's degree in any of the four fields is no longer an option. The next section outlines the choice-specific utility flows.

B. Choice-specific Utility Flows

Bachelor's Degrees. The utility flow of each bachelor's choice across fields is composed of a gender- and type-specific unobserved preference heterogeneity constant and a random choice-specific preference shock. For individual igk, the flow utility from the bachelor's degree in field f at age a is

$$(3) \qquad u_{igka}^{B,f} = \gamma_{\mathrm{g},k}^{B,f} + \varepsilon_{igka}^{B,f}$$

where the error term ($\varepsilon_{igka}^{B,f}$) is an idiosyncratic preference shock. Previous research shows that there is a significant amount of unobserved heterogeneity in students' preference to major in any field (Arcidiacono 2004, Beffy et al. 2012, Gemici and Wiswall 2014, Kinsler and Pavan 2015). To capture such heterogeneity, I assume that there are a finite number of types of college students (three in the estimation for each gender). Students of each type and gender are endowed with a specific preference constant for majoring in each field, $\gamma_{g,k}^{B,f}$. In the data, the field distribution of immigrants differs from that of natives for both genders. To capture the heterogeneity in the degree attainment by demographic group, I allow the probability distribution of types to differ by the individuals' gender and birthplace (i.e. native or foreign-born).[11] The previous research also documents heterogeneity in degree attainment across immigrants from different countries (Bound et al. 2014). However, I do not differentiate immigrants by their country of origin in this study because the number of observations for immigrants is small in the data to make this separation.

Staying at home. The utility flow of staying at home depends on g, a, t, $d_{igk,a-1}^{j,f}$, and a random utility shock (ε_{igka}^{H}) as

[11] Alternatively, I could allow the type-specific preference constant (γ) to differ by birthplace in addition to gender. However, that specification increases the number of parameters to estimate more than the current specification does (i.e., doubles in case individuals' birthplace is grouped as natives and immigrants).

$$(4) \qquad u_{igka}^{H} = \alpha_{1,g}^{H} \, d_{igk,a-1}^{H} + \tilde{\alpha}_{T,g}^{H}(t) + \tilde{\alpha}_{R,g}^{H}(t) \, I_{(a>60)} + \varepsilon_{igka}^{H}$$

where each parameter with ~ is a function of the associated argument (i.e., t in this equation) and $I_{(a>60)}$ is the indicator function for being older than 60. To capture the heterogeneity in preferences across genders, I allow each parameter to be gender-specific. I also assume that each person might get extra benefits ($\alpha_{1,g}^{H}$) if he stayed at home in the previous period. The term $d_{igk,a-1}^{H}$ denotes whether the individual stayed at home in last period. The time-specific component follows a linear trend with a structural break in 1980 as

$$(5) \qquad \tilde{\alpha}_{T,g}^{H}(\mathrm{t}) = \begin{cases} \alpha_{\mathrm{T}1,g}^{H}(t - T_0) & \text{if } T_0 \leq t \leq 1980 \\ \alpha_{\mathrm{T}1,g}^{H}(1980 - T_0) + \alpha_{\mathrm{T}2,g}^{H}\,(t - 1980) & \text{if } 1980 < t \leq T_N \end{cases}$$

where T_0 refers to the initial period in the model and T_N refers to the last period.[12] This specification captures the changing preferences for labor force participation over time because of the evolving social norms about women's role in the labor market and the reduction in costs of childbearing and household maintenance (Eckstein and Lifshitz 2011, Gemici and Wiswall 2014). The utility flow also includes another component as a function of time, which applies only to those older than 60, to explain the observed drop in employment rates after age 60. I assume that

$$(6) \qquad \tilde{\alpha}_{R,g}^{H}(\mathrm{t}) = \alpha_{R1,g}^{H} + \alpha_{R2,g}^{H}\,(t - T_0).$$

This trend captures the changing preferences for retirement due to a combination of factors, including a cohort effect and the rise in social security benefits over time.[13]

[12] The data indicate that the average real earnings of college graduates have grown over time for both genders. For men, the labor force participation rate has been steady, while, for women, it increased until 1980 and then became steady. In a framework with growing earnings and the time-invariant utility of staying at home, over time more people would end up working. Thus, the trend variable is included partially to circumvent this problem. Also, the structural break at 1980 is added to explain particularly the participation pattern of women.

[13] Out of cohort, age, and calendar time effects, only two of them can be identified. I choose to interpret the trend variable as a combination of a cohort and time effect.

Advanced Degrees. The utility of attending school to obtain a master's degree ($j = M$) or a doctorate/professional degree ($j = D$) in field f is composed of the unobserved heterogeneity constant ($\gamma_{\mathrm{g},k}^{j,f}$), a function of time ($\tilde{\alpha}_{T,g}^{j}$), a function of age ($\tilde{\alpha}_{A,g}^{j}$), the costs associated with switching the field of study ($\alpha_{1,\mathrm{g}}^{j,f}$), and an idiosyncratic preference shock ($\varepsilon_{igka}^{M,f}$). If the field (f) of the pursued advanced degree (j) is different than the bachelor's field (i.e., $d_{igk,20}^{B,f} = 0$), then the switching cost is applied at the first year of graduate school because $d_{igk,a-1}^{j,f}$ is zero. Thus, for individual igk at age a, the utility flow is specified as

$$(7) \qquad u_{igka}^{j,f} = \gamma_{\mathrm{g},k}^{j,f} + \tilde{\alpha}_{T,g}^{j}(\mathrm{t}) + \tilde{\alpha}_{A,g}^{j}(a) + \alpha_{1,\mathrm{g}}^{j,f}\left(1 - d_{igk,20}^{B,f}\right)\left(1 - d_{igk,a-1}^{j,f}\right) + \varepsilon_{igka}^{j,f}.$$

Similar to the specification of the utility flow for the bachelor's degree choices, the utility of each advanced degree includes a gender- and field-specific unobserved heterogeneity constant. To capture the field-invariant changes in the preference for attending graduate school, I specify the time-specific component ($\tilde{\alpha}_{T,g}^{j}$) as a linear time trend. This time trend might be due to secular changes in tuition rates and the availability of financial aid. I also assume that the age-specific component of the utility ($\tilde{\alpha}_{A,g}^{j}$) includes linear and quadratic terms for age. In the estimation, I restrict the parameters of the time-specific and age-specific component to be the same for both master degrees and doctorate/professional degrees. In the data, most college graduates hold bachelors and advanced degrees in the same field. To capture this observed pattern, I assume that, if people pursue an advanced degree in a field different from their bachelor's degree, they incur the switching cost in the first year of graduate school. This entry cost parameter might reflect the difficulties of being accepted to those programs and completing the degree successfully for those whose bachelor's studies are in a different field.

Working. The utility flow of working in each occupation choice can be expressed as the summation of a non-pecuniary utility constant ($\alpha_{0,g}^{W,f}$), the costs associated with switching occupation ($\alpha_{1,\mathrm{g}}^{W,f}$), a function of income (Z), and a random utility shock ($\varepsilon_{igka}^{W,f}$). For individual igk at age a, the utility equation for occupation f is specified as

$$(8) \qquad u_{igka}^{W,f} = \alpha_{0,g}^{W,f} + \alpha_{1,\mathrm{g}}^{W,f}\left[1 - \sum\nolimits_{j=W,M,D,B} d_{igk,a-1}^{j,f}\right] + \mathrm{Z}\left(Y_{igkat}^{f}\right) + \varepsilon_{igka}^{W,f}.$$

I assume that a person incurs the entry cost only if he chooses to work in an occupation that is different than the occupation or field of his choice in the previous period. The term inside brackets takes the value of 1 as long as one of the following activities was chosen in the last period: working in a different occupation, studying for a degree in a different field, or staying at home. Each individual takes utility from occupation alternatives by earning income. The function Z converts the dollar amount of earnings in each occupation (Y_{igkat}^{f}) into the units of utility. The data show that the employment rate of the college graduates does not increase noticeably with income. For instance, the labor force participation rates are similar across different education groups despite that advanced degree holders earn considerably more. Thus, I assume that the utility from income differs depending on the income segment as

$$(9) \qquad \mathrm{Z}(Y) = \begin{cases} \alpha_{2,g}^{W}.Y & if\ Y \leq Y_0 \\ \alpha_{2,g}^{W}.Y_0 + \alpha_{3,g}^{W}.(Y - Y_0) & if\ Y_0 < Y < Y_1 \\ \alpha_{2,g}^{W}.Y_0 + \alpha_{3,g}^{W}.(Y_1 - Y_0) + \alpha_{4,g}^{W}.(Y - Y_1) & if\ Y \geq Y_1 \end{cases}$$

where $\alpha_{3,g}^{W}$ is the marginal utility of income in the first line–segment, $\alpha_{4,g}^{W}$ is for the second one, and $\alpha_{5,g}^{W}$ is for the third one. In the estimation, I set the cutoff levels of income at \$45,000 and \$85,000 to be one standard deviation around the mean income observed in the data.

Income. The income in occupation f for individual igk of age a in time t (Y_{igkat}^{f}) is equal to the total number of skill units (S_{igka}^{f}) that the individual has in the associated field multiplied by the price of one skill unit (r_t^f) in that occupation. (See Heckman and

Honore 1990, Heckman et al. 1998, Lee 2005, Lee and Wolpin 2006, Llull 2016 for a similar specification of income as the multiplication of skill units by skill prices.) The amount of accumulated skills depends on the individual's degree attainment, work experience, k, g, and his current idiosyncratic skill shock. The skill accumulation process in field f is specified as

$$(10) \qquad \log S_{igka}^{f} = \sum_{d,m} \beta_{1,d,m}^{f} educ_{igka}^{dm} + \sum_{l} \beta_{2,l}^{f}\, xpr_{\mathrm{igk\alpha}}^{fl} \; + \; \beta_{3,k}^{f} + \beta_{4,\mathrm{g}}^{f} \; + e_{igka}^{f}.$$

$\beta_{1,d,m}^{f}$ represents the contribution of holding degree d in field m on the accumulated skill units in occupation f, while $educ_{igka}^{dm}$ is a dummy variable indicating whether individual igk holds degree d in field m. I model the evolution of work experience with three levels rather than modeling it with the total number of years employed. Because the number of experience levels is smaller than the possible values of years of work experience, this method reduces the size of the state space considerably. The dummy variable $xpr_{\mathrm{igk\alpha}}^{fl}$ indicates whether individual igk has experience at level l in occupation f. Thus, $\beta_{2,l}^{f}$ captures the effect of having experience level l in occupation f on the total skill units in the same occupation. I assume that the occupation-specific work experience increases to the next level with a certain probability only for those who choose to work in that occupation, and I estimate the occupation-specific probability of moving up to the higher level. Viewing increases in work experience as a stochastic event implies that a worker faces wage increases once in a while with each promotion to the next level of work experience. This pattern in wage growth might reflect the reality better than actual years of experience do as the latter implies wage increases with certainty for each additional year worked. On the other hand, I assume that the skill units obtained by working in an occupation depreciate fully when a person switches to another occupation.[14] Finally, $\beta_{3,k}^{f}$

[14] It is theoretically possible for the depreciation rate to be in the range of 0 to 1. Identifying the depreciation rate is not possible with the available data, which provide each individual's employment and earnings for only two consecutive periods. Because the assumption of full depreciation reduces the size of the state space, I assume the depreciation rate to be 1. Other papers with a similar size of state space adopt the full depreciation assumption as well because it is computationally expensive to make an estimation otherwise (e.g., Sullivan 2010). Moreover, Bronson (2015) documents large depreciation in human capital of college graduates. For

denotes the skill endowment of type k people in occupation f, $\beta_{4,g}^{f}$ is the skill constant associated with being a woman in occupation f, and e_{igka}^{f} is an idiosyncratic skill shock.

Shocks. Each flow utility and skill accumulation function includes a shock. I assume that each person learns the values of these shocks at the beginning of each period, but he faces uncertainty about their future realizations. I assume that the preference shocks are distributed i.i.d. extreme value, with the distribution function $F(\varepsilon) = \exp\{-\exp(-\varepsilon/\tau)\}$ where τ is the scale parameter of the distribution. On the other hand, I assume that the skill shocks follow a normal distribution with mean zero. I set the off-diagonal elements of the covariance matrix to zero and estimate the diagonal elements. I assume that the standard deviation of skill shocks in each occupation follows a separate linear time trend as assumed in Lee and Wolpin (2010).

C. Aggregate Production Function

I specify the aggregate production technology as a nested constant-elasticity-of-substitution (CES) function,

$$Q_t = A_t \; [\theta_{Lt} L_t{}^{\omega_L} + (1-\theta_{Lt})\, H_t{}^{\omega_L}\,]^{1/\omega_L} \tag{11}$$

where Q_t is the total output produced in the economy at time t, A_t is the total factor productivity, L_t is the aggregate amount of low-skilled labor, and H_t is the aggregate amount of the skilled composite input.[15] The variable θ_{Lt} denotes the factor share of the low-skilled labor, and $1/(1-\omega_L)$ is the elasticity of substitution between the low-skilled labor and the skilled composite input. The composite input includes capital (K) and four types of high-skilled labor: business (B), engineering (E), science (S), and "other"

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instance, she shows that working part-time or taking a year off decreases earnings from about 16% to 21% in science/business occupations.

[15] I choose the CES form among other commonly used linearly homogeneous production functions including the trans-log and the Cobb-Douglas because the CES has few parameters to estimate compared to the trans-log and does not restrict the elasticity of substitution to be 1 as the Cobb-Douglas does, although it still imposes a constant elasticity of substitution. Moreover, Krusell et. al. (2000) and Lee and Wolpin (2006) explain the aggregate output data reasonably well with a CES form. Thus, I follow their strategy. See Fare and Mitchell (1989) for a discussion of more flexible forms of production technology.

skills (O).[16] The aggregate amount of each type of high-skilled labor is measured in skill units as the sum of the skills of all college graduates who work in the related occupation. This measurement approach is equivalent to papers that weight the number of skilled and unskilled workers with the associated efficiency units (e.g., Katz and Murphy 1992, Krusell et al. 2000), but it allows for a continuum of skill units across workers, depending on each person's education, work experience, gender, and unobservable characteristics. The composite input is specified as

$$H_t = \left(\sum_{F \,\epsilon\, \{K,B,E,S,O\}} \theta_{Ft} {F_t}^{\omega_H} \right)^{1/\omega_H} \tag{12}$$

where F_t represents the aggregate amount of input F at time t, θ_{Ft} is the time-varying factor share associated with input F, and $1/(1-\omega_H)$ is the elasticity of substitution between the factors in the skilled composite input. This nesting structure allows some flexibility in estimating the capital–skill complementarity. For instance, if ω_H is estimated to be lower than ω_L, then capital is less substitutable with (i.e., more complementary to) the high-skilled labor types than it is with the low-skilled labor.

Each factor share follows a separate linear time trend with a structural break in 1980 as

$$\theta_{Ft} = \begin{cases} \theta_{0,F} + \theta_{1,F}\,(t - T_0) & \text{if } T_0 \leq t \leq 1980 \\ \theta_{0,F} + \theta_{1,F}\,(1980 - T_0) + \theta_{2,F}\,(t - 1980) & \text{if } 1980 < t \leq T_N. \end{cases} \tag{13}$$

This specification allows for the possibility of the "skill-biased technological change" (Katz and Murphy 1992, Acemoglu 2002) if the factor share of the low-skilled labor is

[16] Griliches (1969) finds capital to be more complementary to high-skilled labor than it is to low-skilled labor. Following him, researchers use a nested production function to allow the elasticity of capital to vary with labor of different types. For instance, Goldin and Katz (1998), Krusell et al. (2000), and Lee and Wolpin (2006) specify a production function with capital and high-skilled labor in the inner nest as I do in this paper. Unlike the existing papers, I define four types of high-skilled labor and nest all of them with capital in the same level. As a result, this nesting structure imposes the same elasticity of substitution between low-skilled labor and each type of high-skilled labor. On the other hand, Lewis (2011) and Autor et al. (2003) nest capital and low-skilled labor in the same nest. Given the variety of specifications in the literature, different nesting structures might be explored in future research as a robustness check.

estimated to decrease over time.[17] Furthermore, the production function is subject to constant returns to scale because I normalize the factor share of "other" skills such that the sum of the factor shares in the composite input equals to 1 in every period (i.e. $\theta_{Ot} = 1 - \sum_{F\epsilon\{K,B,E,S\}} \theta_{Ft} \quad \forall t$). The value of each factor share is also between zero and one by definition.[18]

D. Equilibrium

Equalizing the marginal product of each factor to its rental price determines the aggregate demand for each factor. I assume that capital and low-skilled workers are perfectly elastically supplied at their level of rental prices observed in the data. On the other hand, the supply of each type of high-skilled labor is equal to the aggregation of the skill units of all college graduates working in the relevant occupation. The rental price of each high-skilled labor type is determined as an outcome of the market-clearing process. A rational-expectations equilibrium is defined as a sequence of the skill prices $\{r^*_{Mt}, r^*_{Et}, r^*_{St}, r^*_{Ot}\}_{t=1}^{T}$ such that:

1) College graduates make their optimal decisions based on these prices, and

2) The skill markets clear every period at these prices (i.e., the quantity demanded for each type of skilled labor is equal to the quantity supplied).[19]

[17] Autor, Murnane, Levy (2003) link the increasing IT investment with the replacement of workers performing the routine tasks. They claim that the proliferation of computers in work places (starting in the 1980s) changes the structure of the labor demand. In order to capture such a change, I assume a piece-wise linear functional form with a structural break in 1980 for the factor shares, which is similar to that of Lee and Wolpin (2006).

[18] In the estimation, I obtain the parameter estimates satisfying these restrictions as follows. I define new variables to estimate factor shares in the initial, break, and final period of the model: $\tilde{\theta}_{F,T_0}, \tilde{\theta}_{F,1980}, and\ \tilde{\theta}_{F,T_N}$. I estimate each of these new variables without any restriction. I obtain the estimates of the factor shares in equation (13) from a non-linear transformation of the estimates of the new variables. For instance, I obtain the share of low-skilled labor as $\theta_{L,t} = \frac{\exp(\tilde{\theta}_{L,t})}{1+\exp(\tilde{\theta}_{L,t})} \ \forall t \in \{T_0,\ 1980,\ T_N\}$, which ensures that the factor share is between 0 and 1 in these years. Then I calculate the trend variables associated with the period before 1980 as $\theta_{1,L} = (\theta_{L,1980} - \theta_{L,T_0})/(1980 - T_0)$ such that the factor share will be between 0 and 1 in every year until 1980.

[19] Flinn (1993) develops a similar equilibrium model where agents of overlapping generations decide on schooling with perfect foresight about the future cohort sizes. He shows that the equilibrium exists and is unique.

IV. Model Solution

The model solution can be divided into two parts. In the first part, I solve the utility maximization problem of an individual at a given set of skill prices. Because it is a standard finite-horizon dynamic discrete choice problem, I apply the backward recursion method. I then measure the aggregate supply of each skill type in the overall economy. In the second part, I find the set of skill prices which satisfies the equilibrium conditions. For that purpose, I iterate over skill prices while solving the utility maximization problem at each iteration until the market for each skill clears.

A. Solving the Utility Maximization Problem

Each individual maximizes the discounted present value of his expected lifetime utility. Let $V(\Omega_a)$ denote the maximized expected lifetime utility of an individual of age a with the state vector Ω_a. (Note that I suppress the indices of i, g, and k in each relevant term for brevity of notation throughout this section). The lifetime utility can be formalized as

$$(14) \qquad \mathrm{V}(\Omega_a) = \max_{d_a^{j,f} \in \Psi(\Omega_a)} V^{j,f}(\Omega_a) = \max_{d_a^{j,f} \in \Psi(\Omega_a)} \left(u_a^{j,f}(\Omega_a) + \delta\, E[\,\mathrm{V}\,(\Omega_{a+1})]\right)$$

where $V^{j,f}$ is the choice-specific value function associated with choosing alternative j in field f, $u_a^{j,f}$ is the associated flow utility, δ is the discount factor, and Ω_{a+1} is the next period's state that evolves according to the current choice. The state vector of an individual consists of the unobserved heterogeneity type, gender, post-secondary degree endowment, work experience, choice in the last period, and current idiosyncratic preference and skill shocks as well as calendar time and the sequence of equilibrium skill prices from his current age to retirement.[20] Degree endowment evolves deterministically

[20] Although the value function depends on each individual' type and gender, they do not increase the possible values of the state space because they are fixed over time.

depending on the choice of degree alternatives.[21] Work experience evolves randomly if an occupation alternative is chosen. I assume that each agent knows the probability that work experience increases to the next level. I also assume that each individual knows his type and observes the values of current idiosyncratic preference and skill shocks at the beginning of each period before making a decision. Thus, he faces uncertainty about future realizations of preference and skill shocks.

I also assume that each individual has perfect foresight about the sequence of future skill prices. In the context of this model, the assumption of perfect foresight implies that people need to know future realizations of aggregate variables, including the number and the skill composition of immigrants, the population of native cohorts, the rental price of capital and low-skilled workers, and parameters of the aggregate technology. An alternative assumption to perfect foresight might be to specify a forecasting rule for the sequence of each of these aggregate variables. As a sufficient statistic to capture the evolution of all aggregate variables, some researchers specify a forecasting rule only for future skill prices (e.g., Lee and Wolpin 2006, Llull 2016). Because this approach complicates the estimation and requires the specification of an ad hoc forecasting rule, I follow the literature that relies on the perfect foresight assumption (e.g., Flinn 1993, Lee 2005, and Gemici and Wiswall 2013).

Conditional on the sequence of skill prices that are realized until age 65, each agent faces a finite-horizon dynamic programming problem.[22] I solve this dynamic programming problem recursively starting from calculating the value function at age 65. Because I assume that each individual dies at the end of age 65, each choice-specific value function at that age, $V^{j,f}(\Omega_{65})$, is equal to the flow utility of the associated

[21] If a person chooses one of the degree alternatives, then he attends school until obtaining the degree pursued. In the estimation, I assume that it takes two years to complete master's degrees regardless of the field of study, three years for professional law degrees, six years for doctorate degrees in science and engineering, four years for professional medical degrees, and six years for doctorate degrees in the other fields.

[22] The evolution of aggregate state variables after age 65 might affect the utility flows of choices made before age 65. For instance, the expectation of an event in the future (such as an influx of immigrants after age 65) might change younger people's labor supply behavior and current skill prices. As a result, future events might also affect the behavior of older people because of changes in current skill prices even though older people do not experience the event during their life cycle. However, including the sequence of skill prices that are realized until age 65 into the state variables captures the effect of possible future events. Thus, the problem can be described as a finite-horizon one.

choice.[23] The key challenge is to calculate the expectation of the value function (i.e.,$E[\,\mathrm{V}\,(\Omega_{65})]$), yet the distributional assumption about the preference shocks simplifies this process as described below. Each choice-specific value function of age 64 is the flow utility of the choice at age 64 plus the discounted expected value function of age 65 at the state that the choice at age 64 implies. Thus, knowing the expected value function of age 65 at every possible state, I can calculate the expected value function of age 64. I repeat this process recursively until the initial age 20.

The assumption that preference shocks follow the extreme value distribution implies that the expected value function at state Ω_a takes a closed-form solution conditional on the associated vector of skill shocks (e_{Ω_a}), and the vector of type-specific preferences and skill endowments, $\gamma_{\Omega_a} = \left\{\gamma^{B,B}_{\mathrm{g},k}, \ldots, \gamma^{D,O}_{\mathrm{g},k}, \beta^{B}_{3,k}, \ldots, \beta^{O}_{3,k}\right\}$. This closed-form solution is

$$(15) \qquad E\left[\mathrm{V}(\Omega_a)|\, \gamma_{\Omega_a}, e_{\Omega_a}\right] = \tau\left(\gamma + \ln\left[\sum_{d_a^{j,f} \in \Psi(\Omega_a)} exp\left(\frac{\overline{V}^{j,f}(\Omega_a \mid \gamma_{\Omega_a}, e_{\Omega_a})}{\tau}\right)\right]\right)$$

where τ is the scale parameter of the extreme value distribution, γ is Euler's constant, and $\overline{V}^{j,f}$ is the deterministic portion of the choice-specific value function, which is defined as $V^{j,f}(\Omega_a) - \varepsilon^{j,f}_{\Omega_a}$.

I obtain the unconditional expected value function by integrating over the distribution of skill shocks,

$$(16) \qquad E\left[\mathrm{V}\big(\Omega_a|\, \gamma_{\Omega_a}\big)\right] = \int E\left[\mathrm{V}\big(\Omega_a|\, \gamma_{\Omega_a}, e_{\Omega_a}\big)\right] f(e_{\Omega_a})\, de_{\Omega_a}$$

[23] To impose this assumption, I set the utility flow of each alternative after age 65 to zero in the estimation. This restriction is not realistic because people might live longer than 65 years and the utility after that age might depend on the choices made in previous periods. However, the turnpike theorem shows that the optimal path of choices in a dynamic model with long horizon is close to the optimal path implied by a model of longer horizon (McKenzie 1976). In the context of my model, this result suggests that each individual's choices made in his early career should not be sensitive to the assumption that he dies at age 65 or older.

where $f(e_{\Omega_a})$ represents the density of skill shocks. Because this integral does not have an analytical solution, I simulate it using a finite number of draws from the density of skill shocks, which is a joint normal distribution by assumption.[24]

Applying this solution method requires calculating the expected value function for every possible state. Because the size of the state space is quite large, a computational difficulty arises. I circumvent this problem by using an approximation technique similar to that of Keane and Wolpin (1994). I calculate the expected value function for a subset of states and approximate that for non-simulated states by a regression analysis. A common practice in the literature is to employ state variables in the regression equation as the only explanatory variables. In this paper, I adopt a slightly different regression equation, using the choice-specific value functions. In particular, I estimate the parameters of the following equation by OLS[25]

$$(17) \quad \mathrm{E}\big[\mathrm{V}\big(\Omega_a|\, e_{\Omega_a}\big)\big] - \mathrm{E}\big[\mathrm{V}\big(\Omega_a|\, e_{\Omega_a}=0\big)\big] = \beta_{0\alpha} + \beta_{1\alpha}\, X(\Omega_a)$$

$$+ \beta_{2\alpha}\, [\overline{V}^{best}(\Omega_a|\, e_{\Omega_a}=0) - \overline{V}^{2nd}(\Omega_a|\, e_{\Omega_a}=0)] + \xi_{\Omega_a}$$

where $X(\Omega_a)$ is a set of explanatory variables associated with elements of the state vector Ω_a, the term inside brackets is the difference between the deterministic part of the value function of the best and the second best choice conditional on skill shocks being zero, and ξ_{Ω_a} is an error term.

This specification relies on the following intuition. The expected value function differs from its value calculated with zero skill shocks to the extent that the deterministic component of the best possible choice is close enough to the deterministic part of all the other choices. Otherwise, idiosyncratic skill shocks do not matter. I use the difference

[24] In practice, I use 20 draws for each of the simulated states using antithetic acceleration. This method is known to reduce the variance of simulated objects. See Stern (1997) for a discussion of the simulation methods.

[25] I run the regressions separately for each subset of states indicating the same age, gender, type, and field of bachelor's degrees. The variable $X(\Omega)$ includes a constant, dummies for advanced degrees, dummies for work experience levels, dummies for the choice in the last period, current skill prices in each occupation, interactions of current skill prices with the dummies of advanced degrees, and a linear and quadratic time term.

between the values of the best and second best choice as an explanatory variable in the regression to capture the closeness between the deterministic parts. The approximated value functions based on the estimates of the parameters in equation (17) differ by about 1% on average from the actual values. On the other hand, the approximations that rely only on $X(\Omega_a)$ deviate about 8% on average from the actual values.

After approximating the expectation of the value function at each point of the state space, I calculate the probability of choosing each alternative. The choice probability has a multinomial logit form because of the assumption of the extreme value distribution. In particular, the probability of choosing alternative j in field f for a person with having state vector Ω_a and skill shocks e_{Ω_a} is[26]

$$(18) \qquad \boldsymbol{P}_a^{j,f}\left(\Omega_a \,|e_{\Omega_a}\right) = \frac{\exp(\overline{V}^{j,f}\left(\Omega_a \mid e_{\Omega_a}\right))}{\sum_{d_a^{j,f} \in \Psi(\Omega_a)} \exp\left(\overline{V}^{j,f}\left(\Omega_a \mid e_{\Omega_a}\right)\right)}.$$

B. Simulating the Supply of Skills

I simulate the behavior of individuals in every birth cohort who are alive and between the ages of 20 and 65 from the initial period of the model to the last period. Most individuals enter the model by choosing a college major at age 20, whereas individuals of some cohorts enter the model at an older age.[27] Here, I describe the simulation of the former group as a general case that implies the simulation for the other possibilities. Each

[26] For choices not allowed given the current state, I set $\overline{V}_a^{j,f}(\Omega) = -\infty$. For example, studying for a master's degree is not an option if an individual already has a master's degree or employment is not an option while an individual is studying for a degree.

[27] I estimate the model from calendar year 1960 to 2030. Individuals of some cohorts, such as those born before 1940, enter the model at an age older than 20. I need to know their initial skill endowment. I use the NSCG data to obtain the initial degree endowment from the information of the year of the degree attainment. Yet the work experience is unknown, and I infer that information from the individuals whose employment behavior is simulated in the model. In particular, I assume that the work experience of the cohorts born before 1940 follows the experience distribution of the 1940 cohort. Because each individual of the 1940 cohort accumulates his whole work experience during the period of model solution (i.e., after 1960), I can simulate the distribution of work experience for this cohort. Inferring the older cohort's initial work experience from that information requires the employment behavior of people to be similar around the initial period. The Great Depression might generate some concerns about this assumption. However, previous research shows that college graduates were not affected adversely from the Depression, as their unemployment rate stayed less than 10% during the Depression (Margo 1991). Similarly, some immigrants enter the model at an age older than 20 depending on their age at the arrival into the United States. For these immigrants, I obtain the initial degree endowment from the NSCG and infer the initial work experience information from the existing immigrants of the same birth cohort who arrived in an earlier period.

individual from a cohort of people at age 20 starts the model making a college major choice with the state of no post-secondary degree and no work experience. I obtain the probability of choosing each bachelor's degree from equation (18). After graduation at age 22, individuals of the cohort are scattered over states with different bachelor's degree endowments according to the choice probabilities. From that age onwards, I simulate a finite number of skill shocks for each possible state that people of the cohort are scattered over. Then I calculate the choice probabilities for each simulated value of skill shocks. Next, I update the distribution of people in the cohort over the state space depending on the choice probabilities. I continue to update the distribution by simulating skill shocks and calculating the choice probabilities for each age until the last period.

Let $h_a^{cgkb}(\Omega_a)$ denote the fraction of people holding state vector Ω_a from birth cohort c of gender g, unobserved heterogeneity type k, and birthplace b (i.e., native or foreign-born). Having recovered the values of h_a^{cgkb} for each possible element of the state space, I then calculate the aggregate supply of high-skilled labor of each type as the sum of skill units of all individuals who choose to work in the relevant occupation

$$(19)\quad F_t^{Supply} = \sum_{a=22}^{65} \sum_{g,k,b,\Omega_a} \sum_{n=1}^{N} \frac{Pop_{at}^{cgkb}}{N} \rho^{gkb}\, h_a^{cgkb}(\Omega_a)\, S_a^f(\Omega_a \mid e_{\Omega_a}^n\ )\, \boldsymbol{P}_a^{W,f}\left(\Omega_a \mid e_{\Omega_a}^n\right).$$

Pop_{at}^{cgkb} denotes the population of cohort $cgkb$ at age a in period t, ρ^{gkb} is the probability that an individual of gender g and birthplace b is a type k person, $S_a^f(\Omega_a \mid e_{\Omega_a}^n\ )$ is the amount of skill units in occupation f implied by simulated skill shocks $e_{\Omega_a}^n$, N is the number of simulations for each state, and $\boldsymbol{P}_a^{W,f}$ is the probability of choosing to work in occupation f.[28]

[28] I use the decennial U.S. Census data to obtain the population of college graduates in each cohort. Because I simulate the economy until 2030, I need to know the population of each cohort that will participate in the economy until then. I use the projections provided by the Census Bureau (2012). However, the Census Bureau projections provide the population of the whole birth cohort; it does not separate projections for college-graduates. Thus, I infer the percentage of college-graduates in each cohort from the patterns observed for the recent cohorts in the data. For the cohorts of immigrants, I also assume that the post-secondary degree distribution of the future cohorts follows the distribution for those who arrived in the last decade.

C. Finding the Equilibrium Skill Prices

The previous two sections describe how to find the aggregate supply of skills given a sequence of skill prices. However, skill prices are a function of each individual's optimal decision because the choice of occupation determines the aggregate supply of skills in the economy, thereby changing the unit price of skills. In this section, I describe how I find the equilibrium values of skill prices. I define the algorithm as follows:

1) Start with an initial guess of skill prices in each occupation from period 1 to period T. Let $\vec{R}^0 = \{r^0_{B1}, r^0_{E1}, r^0_{S1}, r^0_{O1}, r^0_{B2}, \dots \dots \dots, r^0_{OT}\}$ denote the initial guess.

2) At these prices, simulate the behavior of individuals in every cohort who are age 20 to 65 from period 1 and period T.

3) Then calculate the aggregate supply of each skill in each period from the sum of skill units of all individuals who choose to work in the relevant occupation as described by equation (19).

4) Find the aggregate amount of capital stock (K_t), the number of low-skilled workers (L_t), and the total factor productivity (A_t) in every period. To do so, solve three equations simultaneously at the levels of the aggregate supply calculated in step 2:

$$(20) \qquad \frac{\partial Q_t}{\partial K_t} = r^{Data}_{Kt}, \qquad \frac{\partial Q_t}{\partial L_t} = r^{Data}_{Lt}, \qquad \text{and} \quad Q_t(A_t) = Q^{Data}_t \quad \forall t.$$

The first two conditions equate the marginal productivity of capital and low-skilled workers to their rental prices as observed in the data.[29] The last condition finds the total factor productivity that makes the aggregate output simulated in the model equal to the output observed in the data.

5) Having recovered the capital stock, the number of low-skilled workers, and the total factor productivity, then plug them into the marginal productivity equation of each high-skilled labor type,

[29] As I will discuss in detail in the identification section, the unit skill prices cannot be separately identified from skill units. I define a unit of low-skilled workers as one full-time full year worker without a college degree. I use the Census and CPS data to calculate the average annual earnings of these workers. I use the average earnings as the rental price of low-skilled workers. On the other hand, I measure the rental price of capital in the data by dividing capital income to capital stock, following Lee and Wolpin (2006). I obtain the series of capital income and stock from the Bureau of Economic Analysis.

$$(21) \qquad \frac{\partial Q_t}{\partial F_t} = r_{Ft} \qquad \forall\, t, F \in \{B, E, S, O\}$$

where r_{Ft} is the rental price of factor F in period t.

6) Let $\vec{R}^1$ be the vector of skill prices implied by equation (21). Note that each individual makes his optimal decision based on the initial prices $\vec{R}^0$. If $\vec{R}^1$ is close enough to $\vec{R}^0$, then $\vec{R}^1$ is the equilibrium set of skill prices. If not, then update the initial guess and repeat the same steps until $\overrightarrow{R}^1$ converges to $\vec{R}^0$.

V. Estimation Method

I estimate the model with the Method of Simulated Moments (MSM). I minimize the distance between the moments of data and simulated counterparts from the model. I use several data sources providing college graduates' characteristics of employment, earnings, career transitions, and post-secondary degree attainment. Table 3 presents the list and source of each moment used in the estimation. In this section, I outline the estimation algorithm, describe the data sources, and discuss identification.

A. Estimation Algorithm

Let φ denote all of the parameters in the model, including the preference parameters and the costs associated with switching career (α's in equations (4) through (9)), the unobserved heterogeneity constants (γ's in (3) and (7)), the parameters of the skill accumulation process (β's in (10)), and the parameters of the aggregate production function (θ's and ω's in (11) through (13)). I start with an initial guess of the parameters, which is denoted by $(\varphi)^0$. Given that guess, I find the equilibrium skill prices as described in the previous section. Let $(R^*)^0$ denote the equilibrium prices associated with $(\varphi)^0$, where $*$ stands for equilibrium. Given $(\varphi)^0$ and $(R^*)^0$, I simulate the moments of interest in the model. Then, I calculate the objective function,

$$(23) \qquad \Gamma(\varphi, R) = \sum_i \left[m_i^{Data} - m_i^{Model}(\varphi, R)\right]^2$$

where m_i^{Data} denotes moment type i in the data and m_i^{Model} its simulated counterpart from the model. Using a derivate-based optimization algorithm, I update $(\varphi)^0$ to $(\varphi)^1$ and find the equilibrium skill prices $(R^*)^1$ associated with $(\varphi)^1$. I keep updating until finding the set of parameters and skill prices that minimize the objective function. Since I calculate the moments of interest from the choice probabilities that are each a continuous function of the model's parameters, the objective function is also a continuous function of the parameters. Thus, I use a derivate-based optimization routine that is known to be faster than simplex algorithms.[30]

B. Data

The Current Population Survey (CPS) collects labor market outcomes of workers over time from a large repeated cross-sectional sample, and I use the CPS as the primary data source in this study. From the 1964-2011 CPS, I calculate the percentage of college-educated people employed in each occupation and the mean and the variance of their annual earnings.[31] I calculate these statistics on the observed characteristics of workers, including sex, age groups (ages between 26-35, 36-45, 46-55, and 56-65), birthplace (by native or foreign-born), and degree level (by the level of highest degree). In addition, I calculate the percentage of people not working after age 60 by workers' age and gender from the CPS data. Moreover, I use the decennial U.S. Census data to calculate the same moments for the years which are not available in the CPS (in particular, all moments in 1960 and the moments by birthplace before 1994).[32]

[30] In practice, I use the optimization method described in Berndt, Hall, Hall, and Hausman (1974) which is commonly known as BHHH in the literature. In contrast, the papers with a similar equilibrium structure (e.g., Lee 2005, Lee and Wolpin 2006, Llull 2016) simulate the behavior of individuals as binary outcomes and calculate the moments of interest as an average of the simulations. The estimation of parameters in these papers must rely upon a simplex optimization routine because their method of simulation generates a discontinuity in the objective function.

[31] Although the necessary information is available in the March supplement throughout the sample period, I instead use the Outgoing Rotation Group (ORG) beginning in1978 to take advantage of its larger sample sizes.

[32] To achieve a certain level of consistency between the statistics calculated from various data sources, I adopt sample restrictions from the previous studies of income inequality which rely on the same data sources (in particular, Autor, Kearney, and Katz 2008). I define those who work at least 1400 hours annually as employed. I exclude the self-employed from the calculation of earning moments because their earnings are not observed in every year throughout the sample period. Moreover, I exclude those with annual income below $4,638 (in 2009 prices) from the calculation of the earning moments, and I multiply the top-coded earnings with 1.5.

The CPS has a short panel feature as it interviews households in its sample in a rotating schedule. In particular, the CPS interviews households in four consecutive months, ignores them for eight months, and interviews the household that live in the same physical home address again in four months. At the end of the fourth month in each cycle, the survey asks earnings. I match the households that are interviewed in two consecutive years, following Madrian and Lefgren (2000). From the matched CPS sample, I calculate the change in the annual earnings of each individual and employ the sample mean and the variance of this statistic in the estimation. I also obtain the proportion of individuals who switch occupation from one year to another from the CPS data.

Because the CPS and the decennial Census do not collect the field of study, I supplement the analysis with the American Community Survey (ACS) and the National Survey of College Graduates (NSCG). The 2009-2011 ACS provides labor market outcomes by the field of bachelor's degrees, while the NSCG (1993, 2003, and 2010) provides them by the field of bachelor's and advanced degrees. I calculate the employment and earnings moments in each occupation conditional on degree type (by level and field), sex, age groups, and birthplace. I also use the NSCG to obtain the percentage of people holding each degree type from each birth cohort of particular gender and birthplace, the proportion of those holding each type of advanced degree conditional on the type of bachelor's degree held, and the moments of graduate school attendance by age groups.

Furthermore, I use the national accounts data from the Bureau of Economic Analysis (BEA). I obtain the series of aggregate output, capital stock, and the rental price of capital from the BEA data, while I use the CPS for the number of low-skilled workers employed in each year and their average earnings.

Because field of study and occupation are provided with a detailed level coding in the data, I need to aggregate them for tractability purposes. I create four career trajectories for each level of degree and occupation: (i) business, (ii) engineering, (iii) science, and (iv) "other." Each aggregated group of the bachelor's and master's degrees includes the following subfields: (i) business and economics, (ii) engineering and computer and physical sciences, (iii) biological and environmental sciences and health-related fields, and (iv) education, social sciences, humanities, and all other fields. I separate engineering fields from biological and related sciences because the share of immigrants in engineering is considerably larger than their representation in the latter (see Table 2); whereas the other structural papers group these two fields together (Arciodocono 2004, Beffy et al. 2012, Gemici and Wiswall 2013, Kinsler and Pavan 2015). On the other hand, I categorize doctoral and professional degrees in each trajectory as follows: (i) professional law degrees and doctorate degrees in business and economics, (ii) doctorate degrees in science and engineering, (iii) professional medical degrees, and (iv) doctorate degrees in all other fields. In this classification, I group the degrees implying similar earning trajectories and immigrant shares together. Lastly, each aggregate occupation category includes the following professional workers: (i) managers, economists, and lawyers, (ii) engineers and computer and physical scientists, (iii) biological and environmental scientists and medical professionals, and (iv) teachers, social scientists, and all other professionals.

C. Identification

A number of normalizations are necessary to achieve identification. First, skill units are not observed in the data, instead I infer them along with skill prices from earnings. To separately identify these two terms, I normalize the level of skill units in each occupation for a group of workers. In particular, I normalize skill units of each type 3 male who has a bachelor's degree in "other" fields, no advanced degree, the first level of work experience, and zero skill shocks to one. I also normalize the nonpecuniary utility constant of staying at home to zero in the initial period and set the extreme value parameter to one because they are not identified (i.e., the variance of preference shocks normalized to $\pi^2/6$). Lastly, I fix the annual discount factor at 0.95, following the prior literature (e.g., Lee and Wolpin 2006, Sullivan 2010, Llull 2016).[33]

The intuition for the identification of the remaining parameters comes from variations in the moments of the data. I use several years of the earnings data from the ACS and the NSCG to identify the parameters of the skill accumulation process. Because these parameters are time-invariant, observing earnings even for one year is enough to identify them.[34] In particular, variations in the mean earnings conditional on the characteristics of workers (degree type, age, gender, and birthplace) identify the parameters governing the impact of the observable variables in the skill accumulation process.[35] Having identified these parameters, the variance of the within-individual annual income differences identifies the variance of idiosyncratic skill shocks. On the other hand, the variance of earnings among the individuals of the same observable characteristics from a cross-sectional sample identifies the type-specific unobserved heterogeneity constants in the skill accumulation process. Unlike the parameters of the skill accumulation process, skill prices change over time and occupations. I use the moments of the mean earnings over time from the CPS and the Census data to identify skill prices (subject to the normalization condition described above).

The identification of the preference parameters comes from variations in the moments of discrete choices. For instance, if the proportion of women working in engineering jobs is smaller than the model would imply based solely on their earnings, then the nonpecuniary utility in engineering jobs should be negative for women. Similarly, the costs associated with switching careers are identified from variations in the moments of career transitions, such as occupation switching, which are not explained solely by income differences. Variations in the degree attainment by gender and birthplace identify the unobserved heterogeneity constants and their distribution. Covariations in the capital

[33] Although it is theoretically possible to estimate the discount factor, researchers report difficulties to obtain convergence with the discrete choice data (e.g., Berkovec and Stern, 1991). Thus, it is a common practice in the literature to fix the discount factor.

[34] See Heckman and Honore (1990) for the proof of identification with cross-sectional earnings data in a similar model where earnings are specified as the multiplication of skill units and skill prices.

[35] Earnings increase with age only through work experience in the model. Even though I do not observe work experience directly in the data, the moments of the average earnings conditional on age groups capture the effect of work experience.

stock, the number of low-skilled workers, and the employment of high-skilled workers identify the elasticity of substitution parameters.[36] Lastly, variations in the income shares of each production factor within the total aggregate output determine the parameters governing the factor shares.

Table 3: List of Moments

Group of Moments	Source
EMPLOYMENT	
Proportion of individuals choosing each occupation	
By year, sex, and 10-year age group	Census, CPS
By year, sex, and level of degree	Census, CPS
By year, sex, birthplace	Census, CPS
By year, sex, 10-year age group, birthplace, and highest degree's field	NSCG
By sex, 10-year age group, birthplace, and bachelor's field	ACS
Proportion of individuals enrolled for each degree	
By year, sex, 10-year age group, and birthplace	NSCG
Proportion of individuals not working after age 60	
By year, sex, and age	Census, CPS
EARNINGS	
Mean and Variance of Annual Earnings in each occupation	
By year, sex, and 10-year age group	Census, CPS
By year, sex, and level of degree	Census, CPS
By year, sex, birthplace	Census, CPS
By year, sex, 10-year age group, birthplace, highest degree's field	NSCG
By sex, 10-year age group, birthplace, and bachelor's field	ACS
Mean and Variance of the Change in Annual Earnings	
By year, sex, 10-year age group, current and last occupation	Matched CPS
CAREER TRANSITIONS	
By year, sex	Matched CPS
By 10-year birth cohorts, sex, birthplace	NSCG
DEGREE ATTAINMENT	
Proportion of individuals obtaining each degree	
By birth cohorts, sex, region of birth	NSCG
AGGREGATE-LEVEL INPUT FACTORS	
Capital stock and the number of low-skill workers, by year	BEA, CPS
The income share of capital and low-skill workers, by year	BEA, CPS
The income share of high-skill labor, by year	BEA, CPS

[36] The previous literature shows that there is inertia in the adjustment of capital and labor levels because of adjustment costs (Cooper and Haltiwanger 2006, Bloom 2009). However, I assume away such adjustment costs because of potential complications in the estimation.

The moments observed in the data might be subject to standard selection issues. A notable example of the selection in the context of this paper emerges in the choice of college major. For instance, people with high aptitude in engineering jobs are more likely to major in engineering and work as engineers than the rest of the population. Thus, the observed earnings in engineering jobs for engineering degree holders might be high due to the effect of the degree on skill accumulation and the unobserved ability of engineers. I rely on some exclusion restrictions to separately identify these two effects. In particular, I use the size and composition of immigration flows as exogenous factors to correct for the selection into majors. Since immigrants change the aggregate supply and the unit price of each skill type, each native cohort faces different income trajectories that depend on the composition and levels of immigration flows.[37] Under the assumption that the variation in immigration is exogenous to natives' preference and ability distribution (that is characterized as stationary over cohorts in the model), immigration serves as an instrument for the choice of college major. This instrument helps to identify the parameters of the skill accumulation process.

The identification assumption fails if the increasing immigration as observed in the data after 1990 was driven by the concurrently declining interest and ability of native students in science and engineering fields. Several policy reports refer to U.S. students' lower scores in international tests compared to those of students from other countries as a sign of the decline in native students' ability in science and engineering fields (National Academy of Sciences, 2005). On the other hand, some researchers find little evidence supporting this claim after interpreting the test scores among top-performing students and looking at the long-run trend in natives' ability and preferences.[38] Nonetheless, the orthogonality assumption between characteristics of immigrants and natives might be relaxed in future research by explicitly modeling immigration as a function of

[37] Beffy et al. (2012) use a similar identification strategy, relying on the variation in returns to college majors due to business cycles in the French economy.

[38] Lowell and Salzman (2008) point out that the share of U.S. students has been consistently large among top performing students in international tests, such as PISA and TIMSS, even though the average score of U.S. students has been lower than many countries. Lowell and Salzman (2007) show that test scores and the number of science and math credits taken in high school have increased over time. Moreover, they show that the percentage of entering freshman class expressing interest to major in science and engineering fields have been remarkably stable over the last three decades.

endogenous factors, such as skill prices, and presumably exogenous factors, such as the increasing number of college graduates in major source countries, international political shocks, and quotas for immigration visas.[39]

Lastly, other exclusion restrictions also help with identification. For instance, the existence of variables in the skill accumulation process that do not enter the utility function, such as work experience, helps to identify the preference parameters. Furthermore, identification of the production function parameters is due to the change in cohort sizes, rental price of capital, and wage of a low-skilled worker.

VI. Estimation Results

In this section, I discuss the parameter estimates. Then, I compare the predicted and actual statistics of college graduates' labor market outcomes, degree attainment, and career transitions.

A. Parameter Estimates

Skill Accumulation Function. Table 4 presents the estimates of the parameters of the skill accumulation process of equation (10) and the associated standard errors. Each parameter can be interpreted as the effect of the associated explanatory variable on the logarithm of the accumulated skill units in the relevant occupation. Alternatively, I can interpret each parameter as the approximate percentage effect on earnings as implied by taking the logarithm of earnings

$$\log Y_{it}^{f} = \log r_t^{f} + \log S_{it}^{f} \tag{24}$$

where r_t^f denotes the unit price of skill f at time t and S_{it}^f the total amount of skill units that individual i holds in that field by time t. I adopt this interpretation in the following

[39] A related concern about the identification arises because of the possibility that the number of immigrants increased in response to labor demand shocks in the U.S. economy. In a commonly-used regression framework, natives' earnings are regressed on a measure of immigration where the effect of labor demand conditions on natives' earnings is absorbed by the error term. To identify the effect of immigration on earnings, immigration must be independent of labor demand conditions. It would otherwise cause an upward bias because of the spurious positive correlation between wages and immigration.

discussion. Also, I refer to occupations in science as “medical” because most professions in this category are health-related.

Because every individual in the model has at least a bachelor’s degree, I have to normalize the effect of one of the bachelor’s degrees to separately identify it from skill prices, and I normalize the bachelor’s degree in “other” fields to be zero in each occupation. The estimated effect of each bachelor’s degree on earnings varies within occupations. For instance, an engineering bachelor’s degree increases the earnings in engineering jobs by 7.6% relative to a bachelor’s degree in “other” fields, a business bachelor’s degree decreases earnings in engineering jobs by 2.3%, and a science degree decreases them by 0.3%. In general, the highest effect in each occupation is found for the bachelor’s degree in the most associated field, except managerial jobs where an engineering bachelor’s degree (6.5%) increases earnings more than a business bachelor’s degree (3.3%).

These estimates of effects of bachelor’s majors are lower than those reported in prior literature. (See Table 8 in Altonji et al. 2015 for a review of the estimates in the literature.) For instance, majoring in engineering is found to increase earnings in the range of 15% to 21% by researchers that control for unobserved heterogeneity in preferences and skill endowment with a structural model (e.g., Arcidiacono 2004, Beffy et al. 2012, Gemici and Wiswall 2014, Kinsler and Pavan 2015). However, unlike the existing literature, I separate the effect of bachelor’s degrees from the effect of advanced degrees and find considerably larger effects for holders of advanced degrees as discussed below. This finding might explain why the estimated effect of each bachelor’s major is larger in the previous studies because it partially captures the effect of advanced degrees.

I find the effects of advanced degrees in every occupation to be positive. The parameter associated with each advanced degree can be interpreted as the percentage effect on earnings compared to not having that advanced degree. Because of the data restrictions, I allow the effect of each degree to differ only by two types of occupations:

the most related one and the rest of the occupations.[40] The estimated effects are similar between the two types of occupations with a slightly higher impact found for the related occupation for most types of advanced degrees. Master's degrees increase earnings in the range of 4.7% to 16.2% with the largest estimate found for the business master's degree. On the other hand, doctorate/professional degrees increase earnings by 16.1% to 60.8%. In particular, the effect of the professional medical degree is noticeably high with a 60.8% premium in the related jobs (i.e., medical), which is consistent with the data indicating high levels of income for physicians.

The reported parameters of work experience in each occupation can be interpreted as the percentage change in earnings if an individual moves to the upper occupation-specific experience level. I normalize the effect of the first level of experience to zero in each occupation for identification. The parameter estimates show that advancing from the first experience level to the second level increases earnings substantially, while moving from the second level to the third implies a decline in every occupation, except the one in "other" professions suggesting a slight increase. For instance, moving to the second level of work experience increases the earnings in management by 56.2%, while moving to the third level decreases them by 15.6%. Because the estimated decline in earnings for moving to the third level is smaller than the increase implied for the second level, the estimates suggest a concave experience-wage profile, which is consistent with the previous literature (e.g., Lee and Wolpin 2010, Gemici and Wiswall 2014, Llull 2016). Moreover, the probability that the level of work experience increases is found to be in the range of 0.011 to 0.046 across occupations. These estimates suggest large changes in earnings of a person only a few times in his life-cycle. Although this pattern might look unreasonable at the individual-level, taking average of earnings over individuals show a gradual increase in earnings with age, as discussed in the section of model fit.

[40] This assumption is equivalent to restricting the effect of each advanced degree to be same in every occupation, other than the most relevant one. I do so because the data are limited to infer a meaningful relationship for every combination of occupation and advanced degrees. For instance, I observe very few lawyers working as engineers in the data, making it infeasible to recover the impact of the professional law degrees on the engineering skills.

Table 4: Skill Accumulation Function Parameters

	Occupations			
Bachelor's Degree	Business	Engineering	Medical	Others
Business	0.033*** (0.011)	-0.023 (0.081)	-0.062 (0.139)	-0.028 (0.030)
Engineering	0.065*** (0.015)	0.076*** (0.020)	0.024 (0.030)	-0.017 (0.027)
Science	-0.009 (0.028)	-0.003 (0.050)	0.089*** (0.029)	-0.029 (0.049)
Other&	0	0	0	0
Master's Degree	Related		Rest	
Business	0.146**	(0.071)	0.162*	(0.090)
Engineering	0.119***	(0.051)	0.115***	(0.047)
Science	0.128	(0.118)	0.093	(0.075)
Other	0.100*	(0.058)	0.047	(0.056)
PhD and Professional Degree	Related		Rest	
Business or Law	0.267***	(0.062)	0.225*	(0.118)
Engineering & Science PhD	0.183	(0.114)	0.161**	(0.081)
Medical	0.608***	(0.078)	0.432***	(0.089)
Others	0.226*	(0.118)	0.172***	(0.073)
Work Experience	Business	Engineering	Medical	Others
Level 1&	0	0	0	0
Level 2 - Level 1	0.562*** (0.104)	0.551*** (0.103)	0.507*** (0.067)	0.459** (0.205)
Level 3 - Level 2	-0.156 (0.117)	-0.155 (0.121)	-0.085* (0.045)	0.037 (0.322)
Probability that the work experience level increases	0.025*** (0.002)	0.025*** (0.002)	0.046*** (0.004)	0.011*** (0.003)
Female Premium	-0.301*** (0.060)	-0.174*** (0.079)	-0.216*** (0.042)	-0.274*** (0.100)
Unobserved Heterogeneity				
Type 1	-0.052 (0.060)	-0.009 (0.057)	0.005 (0.051)	-0.022 (0.161)
Type 2	-0.181*** (0.066)	-0.182*** (0.061)	-0.264*** (0.095)	-0.109 (0.084)
Type 3&	0	0	0	0
SD of Wage Shocks	Business	Engineering	Medical	Others
Base	0.359*** (0.068)	0.270*** (0.102)	0.333*** (0.107)	0.397*** (0.078)
Trend	0.0059*** (0.0002)	0.0018 (0.0015)	0.0035*** (0.0006)	0.0032*** (0.0004)

Note: The table presents parameter estimates for equation (10). The term & indicates that the parameter is restricted at the stated value because of identification. Standard errors are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Table 4 also presents the estimates of type-specific constants for skill endowment. I normalize the constant in each occupation for one type to be zero (in particular, type 3) because it cannot be separately identified from skill prices. The estimates show that a type 1 person has similar levels of skill endowment to a type 3, whereas a type 2 person has fewer skills in each occupation. The results suggest that a type 2 person earns less than a type 3 person by 18.1% in managerial, 18.2% in engineering, 26.4% in medical, and 10.9% in "other" occupations, holding all other explanatory variables constant. The magnitude of these estimates is on par or even higher than the effects of master's degrees, suggesting the importance of unobserved heterogeneity in skill endowment as documented in the literature (e.g., Arcidiacono 2004, Beffy et al. 2012, Gemici and Wiswall 2014, Kinsler and Pavan 2015).

Moreover, the skill constant associated with being a female is estimated to be negative in each occupation. The estimates suggest that women earn less than men by 30% in management, 17% in engineering, 21% in medical, and 27% in "other" professions, holding all other explanatory variables constant. These estimates are similar to those of the literature (e.g., women in white-collar jobs are estimated to earn 29% less than men in Llull 2016 and 27% less in Lee and Wolpin 2006).

Preference and Cost Parameters. Table 5 presents the estimates of the preference parameters of equations (3) through (9). The nonpecuniary utility constant for each occupation alternative is found to be negative for both genders. The negative constants suggest that people take disutility from employment relative to staying at home, as the utility from staying at home is normalized to be zero in the initial period and increases only slightly over time as discussed below. The magnitude of the nonpecuniary constants differs across occupations. Although both men and women experience the least disutility from "other" professions, men most dislike managerial occupations, and women most dislike engineering jobs.

The time trend parameter in the utility flow of staying at home is found to be positive for both genders, suggesting that college graduates enjoy staying at home more over time. In contrast, some researchers find that the utility of staying at home decreases over time for a sample of women including non-college graduates (Lee and Wolpin 2006, Gemici and Wiswall 2014).[41] They interpret this finding as a result of changes in the role of gender in the labor market and the use of birth control. However, the labor force participation of college-educated women increased at a smaller rate compared to that of non-college educated women, even though the earnings of the former increased more over the last five decades. As a result, I find a positive trend in the preference of college-educated women for staying at home. However, the increase in the flow utility due to the trend is small. For instance, for women, the increase experienced from 1960 to 1980 is only about 14% of the nonpecuniary utility constant of employment in "other" professions (i.e., the annual trend of 0.010 times 20 years divided by the nonpecuniary constant 1.45).

Furthermore, the component of the utility flow obtained only by those staying at home after age 60 is found to be almost zero in the initial period, yet it increases over time for both genders. This finding is consistent with the data showing an increase in the early retirement rate of the college-educated people from negligible levels in the initial years of the sample period. The parameter estimates also suggest that the flow utility of attending graduate school increases over time and is a convex function of age. However, the combined effect of the time- and age-specific components on the flow utility is relatively small compared to the magnitude of unobserved heterogeneity constants for degree alternatives as discussed below. Lastly, I find that the estimated marginal utility of income decreases with the income level. For instance, additional $10,000 of income increases the utility from the employment alternatives by 0.736 utils for a man if his income is below $45,000, whereas the same amount of income increases the utility by only 0.259 utils if his income is above $85,000.

To put these estimates into context, I compare the flow utility of working in a managerial occupation to the flow utility of staying at home. For example, for a man with

[41] The effect of calendar time on utility flows can also be interpreted as a cohort effect because the set of cohorts that exist in the economy changes each year. None of the earlier studies or my paper separate these two effects from each other. Thus, although I discuss the effect of this trend variable as a time effect in the main text, it might be interpreted as a combination of a cohort and time effect.

earnings around the sample average in 2009 (i.e., about $100,000 in managerial jobs), the flow utility of working as a manager is 3.24 if he worked in a managerial job last period. This number of 3.24 is obtained as a combination of the nonpecuniary constant and the utility from earnings (i.e., -2.541 + 4.5*0.736 + 4*0.522 + 1.5*0.259). On the other hand, the flow utility of staying at home for the same person is 1.21 as a result of the effects of calendar time on the utility (i.e., 20*0.020 + 29*0.028). Thus, the flow utility of working as a manager is 2.03 larger, which makes the person considerably more likely to continue working as a manager. Such an outcome is consistent with the data because most workers continue to work in the same occupation as discussed in the section of model fit.

Table 5: Preference Parameters

	Male		Female	
Non-pecuniary Intercepts				
Managerial	-2.541***	(0.110)	-2.242***	(0.185)
Engineering	-2.207***	(0.092)	-2.345***	(0.263)
Health	-1.845***	(0.189)	-1.688***	(0.118)
Others	-1.627***	(0.212)	-1.451***	(0.256)
Staying at Home				
Persistence term	0.208	(0.523)	0.354***	(0.054)
Time Trend from 1960 to 1980	0.020	(0.037)	0.010**	(0.004)
Time trend since 1980	0.028	(0.031)	0.022**	(0.011)
Retirement Benefit after age 60				
Constant in 1960	0.001	(0.023)	0.035	(0.483)
Time trend since 1960	0.038	(0.072)	0.025	(0.067)
Preference for Graduate School				
Time Trend since 1960	0.013	(0.010)	0.015	(0.014)
Age/10	-0.025	(0.030)	-0.090***	(0.039)
$Age^2/100$	0.047**	(0.022)	0.046***	(0.017)
Marginal Utility of $10,000 Income				
Less than $45,000	0.736***	(0.073)	0.666***	(0.081)
Between $45,000 and $85,000	0.522***	(0.150)	0.546***	(0.189)
Above $85,000	0.259***	(0.045)	0.266	(0.164)
Extreme Value Parameter$^{\&}$	1			
Annual Discount Factor$^{\&}$	0.95			

Note: The table presents parameter estimates for equation (4) through equation (9). The term & indicates that the parameter is restricted at the stated value because of identification. Standard errors are presented in parentheses. Age is calculated as true age minus 20. Time is calculated calendar time minus 1960. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Table 6 presents the estimated cost parameters associated with career transitions. The cost of entering a new career is found to be large. For instance, the entry cost to managerial occupations is estimated to be 3.10 for men. To put this estimate into context, I consider an example of a job offer in a managerial position with a salary increase from $65,000 to $85,000 for a male worker employed in an engineering job last year. Accepting such an offer increases his utility by 1.04 for each additional year employed (i.e., the estimate of 0.52 for the marginal utility of $10,000 multiplied by 2). Thus, it requires working three years for him to offset the utility cost of entering the managerial occupation. Moreover, the entry cost to each one of the other occupations is estimated to be even larger. On the other hand, I find that the cost of studying for an advanced degree in a field that is different than one's undergraduate major is lower than the cost of switching occupations.

Table 6: Costs of the Entry into a new Career

	Male		Female	
At Labor Market				
Managerial	3.10***	(1.190)	3.63***	(1.403)
Engineering	5.19***	(1.771)	5.44*	(2.791)
Health	3.86*	(2.060)	4.22**	(1.937)
Others	3.45***	(1.427)	3.46***	(1.338)
At Graduate School				
Managerial	0.76	(1.782)	0.94	(1.824)
Engineering	3.77	(3.620)	3.07	(2.176)
Health	1.73	(1.627)	3.00	(2.157)
Others	2.32	(1.936)	3.95	(3.533)

Note: The costs of switching career at graduate school refer to costs of pursuing an advanced degree in a field different from the individuals' bachelors major. The costs at the labor market refer to costs of switching occupations after entering the labor market. Standard errors are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Unobserved Heterogeneity. Table 7 presents the estimates of the type-specific preference constants for degree alternatives of equation (3) and (7) and the distribution of types. Because the choice set of each individual consists of only bachelor's degree alternatives at the beginning of the model, I set each type's preference constant for the bachelor's degree in "other" fields to be zero for identification. The results show that the relative preference to major in business, engineering, or science fields is negative for all unobserved heterogeneity types, except type 1's positive preference for majoring in business.

Table 7: Unobserved Heterogeneity in Preferences for Degrees

	Type 1		Type 2		Type 3	
Bachelor's Degrees						
Business	0.778***	(0.248)	-0.767***	(0.275)	-0.687	(1.159)
Engineering	-0.680**	(0.300)	-1.711***	(0.404)	-2.067	(1.285)
Science	-0.542**	(0.249)	-0.348	(0.231)	-2.235*	(1.286)
Other[&]	0		0		0	
Female Constant	0.089	(0.538)	0.005	(0.151)	-0.433	(1.152)
Master's Degrees						
Business	-4.130*	(2.201)	-5.074	(5.473)	1.789	(1.298)
Engineering	-3.467*	(1.779)	-3.482	(2.344)	2.669	(5.397)
Science	-3.810	(5.717)	-3.121	(2.053)	3.074	(4.607)
Other	-0.223	(1.156)	-2.607***	(0.812)	-0.143	(45.608)
Female Constant	-0.326	(0.452)	0.395***	(0.125)	-4.367**	(1.966)
PhD or Professional Degrees						
Business or Law	-3.828***	(1.259)	-6.596	(18.804)	-3.282***	(0.984)
Science and Engineering	-2.153	(6.137)	-0.423	(0.457)	0.680**	(0.310)
Medical	-7.213	(9.781)	-5.157***	(0.785)	-4.171***	(0.330)
Other	0.044	(1.316)	-0.680	(0.565)	0.447	(0.769)
Female Constant	-0.273	(0.303)	-0.576*	(0.303)	-0.585	(0.519)
Type Probabilities						
Male Natives	0.217***	(0.047)	0.696***	(0.193)	0.087**	(0.039)
Male Immigrants	0.239***	(0.057)	0.645***	(0.228)	0.115	(0.095)
Female Natives	0.148***	(0.022)	0.821***	(0.142)	0.031	(0.023)
Female Immigrants	0.273***	(0.075)	0.653***	(0.226)	0.074	(0.068)

Note: The presented type- and field-specific parameters ($\gamma_{g,k}^{j,f}$) are for males. For females, the parameters are set to $\gamma_{\text{female},k}^{j,f} = \gamma_{g,k}^{j,f} + \gamma_{\text{female},k}^{j}$, where the $\gamma_{\text{female},k}^{j}$ term is presented as female constant in the table. The term & indicates that the parameter is restricted at the stated value because of identification. Standard errors are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Table 8 displays how the estimated heterogeneity in preferences (along with the estimated heterogeneity in skill endowment that changes earnings) reflects on the degree attainment. The estimates show that a type 1 person of both genders is more likely to major in business or engineering fields compared to the other types, a type 2 person is more likely to major in "other" fields, and a type 3 person is more likely to major in science compared to the other types. The estimated distribution of types across gender and birthplace provides some insights into the observed differences in the degree attainment. For instance, type 1's are more likely to major in business or engineering, and they make up 21.7% of native men, 23.9% of immigrant men, 27.3 % of immigrant women but only 14.8% of native women. On the other hand, type 2's are more likely to major in "other" fields, and they make up the vast majority of native women with 82.1% but a relatively smaller share of other demographic groups, such as 69.6% of native men. These estimates are consistent with the data displaying that native women are less likely to major in business or engineering fields compared to native and immigrant males.

The estimated preference constants for advanced degrees suggest substantial variation across different types of people. For instance, a type 3 person enjoys studying for advanced degrees more than the other types and is more likely to hold an advanced degree particularly in business, engineering, or science fields. Because type probabilities vary across natives and immigrants, the estimated variation in these probabilities explains some observed differences in the advanced degree attainment. In particular, I find that immigrant men are the most likely demographic group to be type 3, which is consistent with the data indicating a larger proportion of immigrant men holding an advanced degree.[42] Lastly, the parameter estimates for advanced degrees also indicate some similarities across types. For instance, people of all types experience the highest disutility from a professional law or professional medical degree. Without high levels of disutility, most people would obtain these degrees because the estimated monetary payoff for them is considerably larger than the one for the other degrees.

[42] I should note that the estimated distribution of immigrant types is for the one for foreign college graduates who migrated to the United States. Thus, this distribution might be quite different than the distribution for all foreign college graduates in countries of origin.

Table 8: Degree Attainment by Types

	Type 1		Type 2		Type 3	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Bachelor's Degrees						
Business	0.367	0.297	0.246	0.154	0.326	0.187
Engineering	0.287	0.091	0.181	0.046	0.199	0.069
Science	0.080	0.182	0.102	0.164	0.110	0.195
Other	0.266	0.431	0.471	0.636	0.365	0.549
Master's Degrees						
Business	0.100	0.062	0.050	0.026	0.439	0.313
Engineering	0.070	0.021	0.041	0.016	0.090	0.056
Science	0.011	0.030	0.017	0.044	0.121	0.131
Other	0.205	0.267	0.120	0.240	0.056	0.099
PhD or Professional Degrees						
Business and Law	0.176	0.086	0.011	0.003	0.154	0.156
Science and Engineering	0.004	0.001	0.018	0.004	0.040	0.085
Medical	0.009	0.003	0.027	0.007	0.197	0.244
Other	0.036	0.123	0.021	0.007	0.021	0.115

Production Function Parameters. Table 9 presents the estimates of the production function parameters of equations (11) to (13). The results show a decrease in the factor share of low-skilled labor in line with the hypothesis of the skill-biased technological change (Katz and Murphy 1992, Acemoglu 2002). On the other hand, the factor share of each type of high-skilled labor increases over time. The increase for some types is noteworthy, such as a 5.6% annual growth in the share of business labor until 1980 (i.e., the estimated trend parameter 0.0040 divided by the baseline 0.0714) and a 2.2% annual growth in the share of science labor since 1980. This variation across each type of high-skilled labor suggests that the skilled-biased technological change might affect each college graduate differently depending on his bachelor’s major.

Lastly, I find the elasticity of substitution between capital and high-skilled labor (0.989) to be larger than the one between capital and low-skilled labor (0.595). This result differs from the existing literature that finds that capital is more complementary to high-skilled labor (e.g., Griliches 1969, Krusell et al. 2000, Lee and Wolpin 2006). Unlike these studies, I model high-skilled labor with four types and use only one type of capital instead of differentiating it as structures and equipment capital. These differences in the classification of production factors might be the reason for obtaining different estimates.[43] (See Hamermesh 1986 for a discussion of variation in the estimates of the elasticity of substitution in the literature.)

Table 9: Aggregate Production Function Parameters

Factor Shares	base	trend until 1980	trend after 1980
Low-skill	0.4965***	-0.0027	-0.0020
	(0.1845)	(0.0025)	(0.0019)
Capital	0.7873***	-0.0048***	-0.0017
	(0.2877)	(0.0008)	(0.0014)
Business	0.0714	0.0040*	0.0008
	(0.1177)	(0.0024)	(0.0020)
Engineering	0.0294	0.0003	0.0005***
	(0.0261)	(0.0005)	(0.0002)
Science	0.0187	0.0004**	0.0004
	(0.0389)	(0.0002)	(0.0006)
	Substitution Parameter		
Capital-Low skill	-0.6745***		
	(0.2849)		
Capital-High skill	-0.0112**		
	(0.0058)		

Note: The table presents parameter estimates of the aggregate production function. Standard errors are presented in parentheses. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

B. Model Fit

Employment and Earnings. Each left panel of Figure 2 displays the predicted proportion of people employed across occupations and those observed in the 1964-2010 CPS, and each right panel displays the predicted and observed average earnings. The data show a relatively steady level of employment in each occupation for males, except for a slight decrease in “other” and medical occupations over time and some cyclicality in

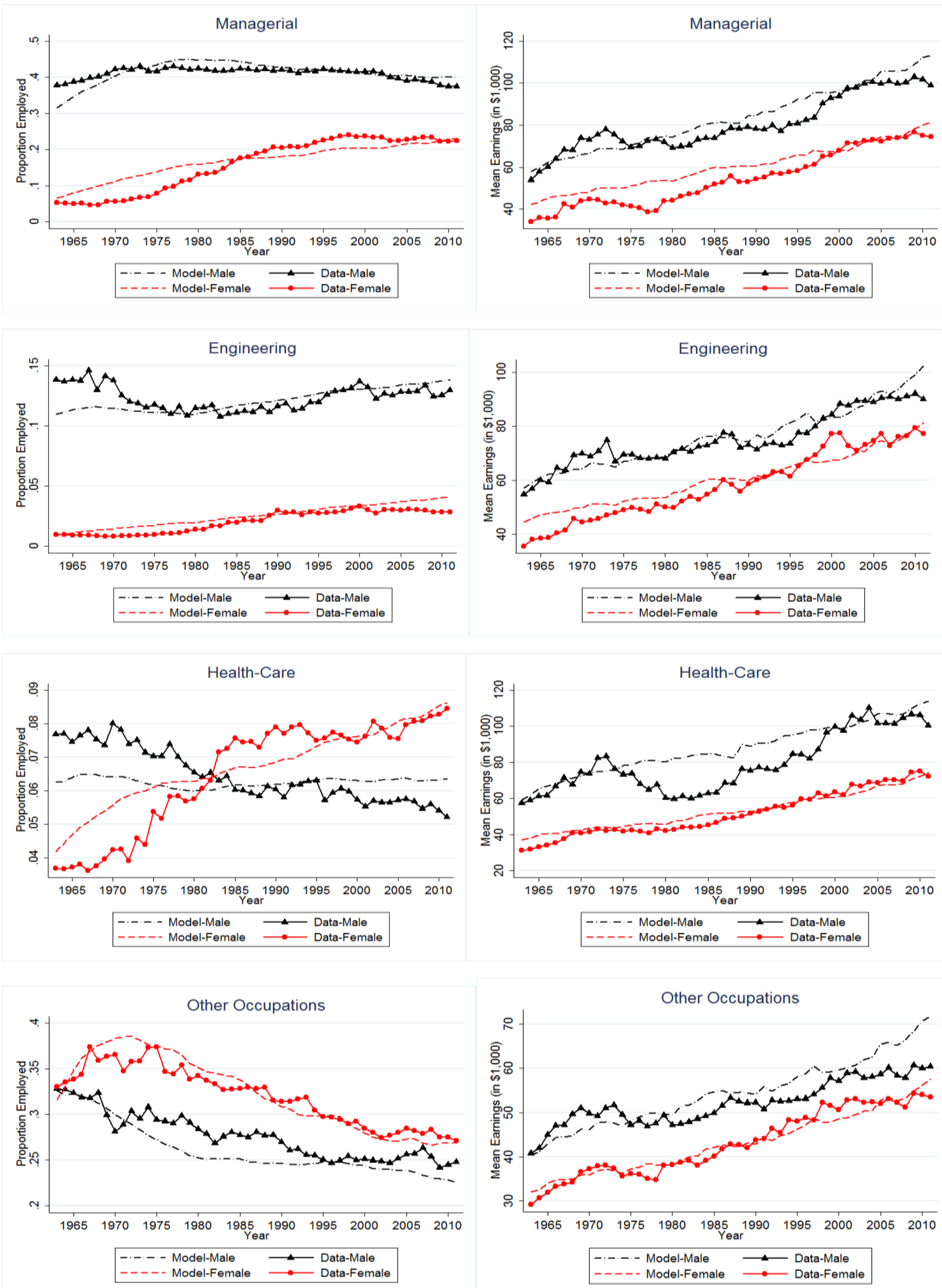
[43] One might also think that differences in assumptions on the functional-form of the production function might cause the differences in the estimates. However, I use the same functional form (a nested constant-elasticity-of- substitution function) by nesting capital and skilled-labor together with, following Lee and Wolpin (2006).

engineering. On the other hand, female employment increases in every occupation, except in “other” professions. The model captures these patterns successfully, but the employment of men is slightly underestimated in engineering and medical occupations for the initial years of the sample.

The data show that the earnings of college-educated workers increase over time in every occupation for both genders. The model captures this increasing trend successfully. The data also show that the earnings gap between men and women declines over time, especially for managers and “other” professionals. However, the model predicts a relatively constant gender gap. Although this prediction is consistent with the assumption that the female constant and the unobserved skill heterogeneity parameter in equation (10) are time-invariant, some discrepancies appear between the actual and predicted values of earnings. For instance, the model overestimates the earnings of women in managerial occupations during the early years of the sample period (about 20% on average until 1980) and overestimates the earnings of men in “others” occupations in recent years (about 10% on average since 2000).

Table 10 compares the predicted employment and earnings conditional on the workers’ highest degree attainment to those observed in the NSCG. The data show that college graduates are more likely to work in occupations closely related to the field of their highest degree, and this pattern is more noticeable among advanced degree holders. On the other hand, total employment does not vary too much with the level of degrees. The model captures these patterns successfully with slightly overestimating the employment of doctorate/professional degree holders. Moreover, the model predicts that average earnings increase with the attainment of advanced degrees in each field, and this prediction is consistent with the observed data.

Figure 2: Model Fit: Employment and Real Earnings



Note: Each left panel displays the predicted proportion of people employed across occupations and those found in the 1964-2010 CPS, and each right panel displays the predicted and observed average real earnings (in terms of 2009 prices).

Table 10: Labor Market Outcomes by Highest Degree Type

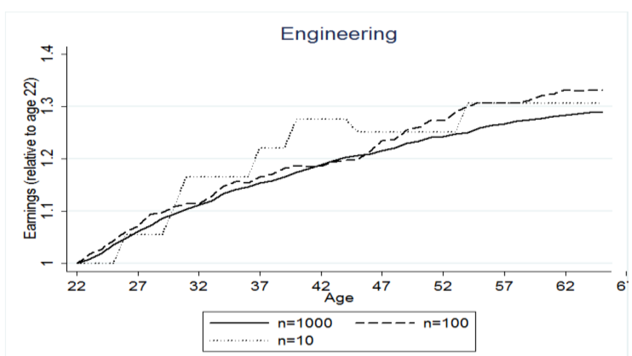
		The Percentage Employed		The Average Earnings (in $1,000)		The Stand. Dev. of Earnings (in $,1000)	
	Occupation	**Data**	**Model**	**Data**	**Model**	**Data**	**Model**
Bachelor's Degree							
Business	Related	60.6	53.5	77.7	84.0	45.3	46.9
	Rest	17.1	19.0	56.1	56.7	28.6	27.8
Engineering	Related	43.5	40.5	82.1	84.1	31.6	37.1
	Rest	37.4	41.4	83.5	79.5	45.3	43.3
Science	Related	35.6	28.9	65.5	62.2	28.6	30.6
	Rest	33.1	37.4	61.9	61.5	35.6	32.7
Other	Related	36.1	34.1	47.9	51.9	25.8	29.2
	Rest	30.8	27.0	64.7	72.1	39.6	38.4
Master's Degree							
Business	Related	60.5	69.3	106.1	100.7	51.3	53.7
	Rest	17.6	19.4	80.0	76.8	35.4	37.1
Engineering	Related	48.8	50.4	93.3	88.7	34.9	39.4
	Rest	30.4	38.7	101.4	89.3	47.5	48.6
Science	Related	37.0	31.4	73.0	65.7	32.3	31.0
	Rest	35.0	39.5	72.8	65.9	32.3	34.8
Other	Related	51.1	50.2	55.5	55.7	21.6	29.1
	Rest	19.0	20.1	74.8	74.9	37.8	38.9
PhD and Professional Degree							
Business and Law	Related	74.6	87.3	117.3	118.0	58.4	58.8
	Rest	7.8	8.7	82.0	95.4	40.7	45.5
Science and Engineering	Related	47.7	50.1	105.7	97.4	41.2	45.3
	Rest	38.2	40.3	95.8	92.9	43.4	49.9
Medical	Related	74.8	86.9	140.8	124.3	61.2	59.0
	Rest	9.6	11.3	130.9	129.5	59.5	60.6
Other	Related	55.5	61.4	69.1	70.3	30.8	37.7
	Rest	23.2	25.5	107.6	95.0	48.1	48.3

Note: The statistics of earnings are presented in real terms (in 2009 prices).

Whether the model captures the relationship between earnings and age is another aspect of the model fit. Work experience is the only variable that would affect earnings as each person gets older, holding all other explanatory variables constant. Remember that I model the evolution of work experience with only three levels, and the estimates suggest a large increase in earnings with moving to the second level and a smaller decrease with moving to the third one. For instance, a recently-graduated engineer with the earnings of $62,000 (the average value observed in the data) faces about a $34,000 increase in his earnings if he gets promoted to the second level of work experience (i.e., a 55.1% increase). On the other hand, moving to the third level decreases his earnings from $96,000 to $81,000 (i.e., a 15.5% decrease).

Such a decline in earnings at the individual-level might look unreasonable; yet aggregating changes in earnings over individuals evens out these large declines that are experienced by a fraction of workers. Figure 3 displays the profile of age and average earnings in engineering with a different number of simulated earnings patterns. As the number of simulations increases, average earnings become a smoothly concave function of age. Such a concave relation is also found by the researchers who model work experience with a number of years worked (e.g., Lee and Wolpin 2010, Gemici and Wiswall 2014, Llull 2016).

Figure 3: The Relationship between Age and Earnings



Note: I simulate work experience levels for a sample of workers according to the estimated probability of promotion in engineering occupations. Each line shows the average earnings at each age relative to that of age 22 based on a different number of simulations.

Degree Attainment. Table 11 compares the predicted proportion of natives holding each type of post-secondary degree to that found in the NSCG. The data show that the field distribution of the bachelor's degrees for native men is relatively stable from the cohorts born in the 1940s to those born in the 1980s. Yet, the proportion of native females majoring in each of business, engineering, or science fields increases substantially from the cohorts born in the 1940s until those born in the 1960s, while the proportion of those majoring in "other" fields declines. The model successfully captures these general patterns observed in the data. Moreover, the field distribution of advanced degrees reflects the patterns observed at the bachelor's level. For instance, the proportion of those holding advanced degrees in "other" fields decreases over time in line with their declining share at the bachelor's level, and the model captures this noticeable decline.

Table 11, Panel A: Degree Attainment of Native Men (in percentages)

		Bachelor's		**Master's**		**PhD/Professional**	
Cohorts	**Field**	**Data**	**Model**	**Data**	**Model**	**Data**	**Model**
1940-1949	Business	26.9	29.8	9.4	8.9	5.7	5.7
	Engineering	20.5	17.2	5.7	3.8	2.5	2.0
	Science	9.3	8.3	2.3	3.1	4.0	3.5
	Other	43.3	44.6	19.1	17.1	3.6	3.8
1950-1959	Business	27.4	29.9	8.9	9.4	4.6	6.8
	Engineering	20.1	18.7	4.6	4.9	1.7	2.0
	Science	11.4	8.8	2.2	3.0	4.4	3.5
	Other	41.1	42.6	12.9	15.4	2.0	3.0
1960-1969	Business	31.4	27.0	9.5	10.1	4.0	7.0
	Engineering	23.9	20.2	4.7	6.2	1.4	1.7
	Science	9.1	9.8	1.8	2.7	3.3	3.9
	Other	35.7	43.0	8.8	12.4	1.0	2.3
1970-1979	Business	26.7	26.0	7.6	10.9	4.2	5.5
	Engineering	20.0	21.5	3.4	6.4	1.4	0.9
	Science	10.7	10.4	1.8	2.1	3.3	4.1
	Other	42.6	42.2	11.3	8.3	0.8	1.3
1980-1985	Business	27.0	26.4	x	x	x	x
	Engineering	20.4	23.2	x	x	x	x
	Science	9.5	10.8	x	x	x	x
	Other	43.1	39.6	x	x	x	x

Table 11, Panel B: Degree Attainment of Native Women (in percentages)

		Bachelor's		Master's		PhD/Professional	
Cohorts	**Field**	**Data**	**Model**	**Data**	**Model**	**Data**	**Model**
1940-1949	Business	8.5	13.7	2.5	3.9	1.7	1.2
	Engineering	3.2	3.9	1.1	1.7	0.7	0.6
	Science	13.6	14.4	4.2	4.7	0.6	0.6
	Other	74.7	68.0	33.3	34.1	3.0	4.6
1950-1959	Business	15.1	16.1	4.3	4.3	2.6	1.6
	Engineering	4.2	4.6	1.2	2.2	0.7	0.7
	Science	18.5	15.3	4.8	4.9	1.5	1.0
	Other	62.3	63.9	23.2	30.4	1.6	3.8
1960-1969	Business	24.7	17.4	4.5	4.5	2.9	2.2
	Engineering	6.4	5.6	1.4	2.5	0.6	0.6
	Science	16.6	16.4	3.5	4.9	1.6	1.5
	Other	52.3	60.6	15.4	24.3	1.0	2.9
1970-1979	Business	19.0	18.8	3.8	4.0	3.2	2.5
	Engineering	5.1	6.7	1.0	2.4	0.7	0.5
	Science	17.2	17.8	4.1	4.0	2.1	1.9
	Other	58.7	56.6	18.5	16.4	0.8	1.5
1980-1985	Business	17.4	19.8	x	x	x	x
	Engineering	5.0	7.4	x	x	x	x
	Science	16.8	19.1	x	x	x	x
	Other	60.8	53.8	x	x	x	x

Note: Because the attainment of advanced degrees is calculated for those older than 30, the 1980-1985 birth cohorts do not have the relevant information by 2010.

However, the data show a slight cyclicality in the field distribution of the bachelor's and advanced degrees. In particular, the proportion of those majoring in business or engineering peaks for the native cohorts born in the 1960s for both genders, and then it becomes lower for recent cohorts. In contrast, the model predicts a secular trend in the attainment of degrees in each major over cohorts. The structure of the model might provide some explanations on why it fails to capture the cyclicality. In particular, the model includes only a few explanatory factors that would vary across fields over time and create cyclicality in natives' choice of college major: the population and the composition of immigrants. On the other hand, some preference parameters and the factor shares in the production technology follow a linear time trend. Moreover, I assume that the distribution of types governing unobserved heterogeneity in preferences for degrees and skill endowment is constant over cohorts of the same of gender and birthplace. In such a setup, the model fails to capture the cyclicality in the field distribution. Although variation in immigration explains the decline in recent cohorts' attainment of engineering degrees to some extent as discussed in more detail in next section, it is not enough to match the cyclicality observed in the data. To capture the cyclicality, introducing field-specific shocks to the aggregate production function or allowing the distribution of preference and skill constants to vary with time as a function of some explanatory variables, such as test scores, might be the direction of future research.

As discussed before, unobserved heterogeneity plays a significant role to explain differences in degree attainment of college graduates with different demographic characteristics. Remember that I model unobserved heterogeneity with only three types and allow each type to have different preferences and skills in each field. However, this assumption can reflect only a small number of combinations in preferences and skills. In particular, I find that a type 1 person has high levels of ability in each occupation, and he is inclined to major in business or engineering but not likely to pursue an advanced degree. A type 3 person has preferences and skills similar to a type 1 person, except that he is more likely to study advanced degrees. In contrast, a type 2 person has less ability in each occupation and is more likely to major in "other" fields than the other types. Even though each unobserved heterogeneity type describes a certain pattern of schooling and earnings behavior, some other patterns that are not captured with the current estimates might exist. For instance, some type of people might be talented only in certain fields. A version of the present model with a larger number of unobserved heterogeneity types can be estimated in future research to assess whether the model fit can further be improved.

Career Transitions. Table 12 compares the predicted values of career transitions realized in the labor market and graduate school to those found in the CPS and the NSCG. The data show a high level of persistence in the occupation choice with more than 80% of college graduates continuing to work in the same occupation from one year to another. Similarly, most college graduates pursue an advanced degree in a field closely associated to their bachelor's major, yet the observed persistence in the degree choice is smaller than the one in the occupation choice. For instance, only about a half of business master degree holders major in business fields at the bachelor's level in the data. The model captures both types of career transitions closely.

Table 12: Career Transition

Current Choice \ Last year's choice	Business		Engineering		Medical		Other		Home	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Business	84.0	83.6	1.9	2.7	1.3	2.5	2.2	3.7	6.3	12.4
Engineering	0.4	0.3	82.1	84.9	0.5	0.3	0.5	0.4	1.7	1.4
Medical	0.5	0.5	0.7	0.4	81.7	83.8	0.5	0.5	2.1	1.9
Other	2.4	3.0	2.6	2.1	1.6	2.3	81.2	81.9	9.8	12.2

Bachelor's Field \ Master's Field	Business		Engineering		Science		Other	
	Data	Model	Data	Model	Data	Model	Data	Model
Business	50.4	52.9	7.7	3.2	3.6	4.4	6.9	10.1
Engineering	21.4	11.8	79.0	83.9	7.0	4.0	4.3	3.6
Science	6.6	4.2	4.6	2.8	68.8	73.1	5.2	2.0
Other	24.8	31.0	11.3	10.2	24.3	18.5	84.3	84.3

Bachelor's Field \ PhD's Field	Business & Law		Engineering		Medical		Other	
	Data	Model	Data	Model	Data	Model	Data	Model
Business	91.4	88.5	1.2	3.2	3.2	1.3	4.3	6.0
Engineering	6.1	10.2	49.9	57.7	12.9	3.7	4.0	1.7
Medical	4.0	1.3	42.2	28.4	70.8	74.9	4.4	1.4
Other	x	x	9.4	10.8	14.7	20.0	88.3	90.9

Note: The first category of PhD/Professional degrees includes both business doctorate and law professional degrees. Because holders of professional law degrees are more likely to major in "other" fields at the undergraduate level, I match the combined share of transitions from business and "other" bachelor's degrees to business doctorate and professional law degrees.

VII. The Effects of Immigration

In this section, I present counterfactual simulations to assess the effects of immigration. In the model, immigrants affect natives' degree attainment and labor market outcomes through their impact on the aggregate supply of skills because the supply affects equilibrium skill prices. To quantify the effects of immigration, I simulate the economy by restricting the supply of high-skilled immigrants. In particular, I set the population of immigrant cohorts that entered to the United States after 1960 to zero. Then, I simulate natives' and remaining immigrants' behavior and find the associated equilibrium skill prices at this counterfactual level of population, holding all other parameters constant.[44]

I need to specify how the stock of other factors of production (i.e., capital and low-skilled labor in this paper) evolves with respect to a change in the supply of immigrants. Following Ottoviano and Peri (2012), I assume that the unit rental price of capital and the wage of low-skilled workers stay the same at their values observed in the baseline economy. This assumption is equivalent to suppose that the stock of capital and the employment of low-skilled workers adjust quickly in response to a change in the number of high-skilled immigrants such that the marginal productivity of each factor stays equal to the rental prices realized in the baseline economy.[45] I assume away the possibility that changes in the counterfactual levels of capital and low-skilled labor might affect their rental prices. Taking these effects into consideration requires modeling the supply of capital and low-skilled labor, which is beyond the scope of this analysis.

A. The Effect of Immigration on Natives' Outcomes

Labor Market Outcomes: Table 13 shows the percentage change in natives' labor market outcomes with respect to the baseline economy. The results indicate that the proportion of college-educated natives employed in engineering and medical occupations would have increased respectively by 8.1% and 6.8%. On the other hand, native employment in managerial and "other" occupations would have declined respectively by 0.6% and 2.8%. Because the proportion of natives working as scientists and engineers is

[44] In particular, I keep constant the parameters of preferences, career switching, the skill accumulation process, and the aggregate production function. I use the same idiosyncratic skill shocks in baseline and counterfactual simulations. Also, I calculate the sequence of aggregate shocks in the baseline economy (i.e., A_t) as described in Section IV and use the same sequence in counterfactual simulations.

[45] I also simulate the effects of immigration by holding the stock of capital and the number of low-skilled workers constant. The estimated effects under this assumption can be interpreted as short-run effects where adjustments in the level of capital and low-skilled labor are not possible. The results under this assumption show that the earnings of college-educated natives would have increased by 5.81% on average with a 5.80% increase in engineering and a 8.60% increase in in medical occupations. These figures are larger than the estimated effects with the assumption of full adjustment (a 0.24% increase on average as I discuss in detail below).

low in the baseline economy, the estimated larger percentage increase for science and engineering employment would have been offset by the estimated decrease in the rest of the occupations. As a result, the total number of working college-educated natives would have increased only by 0.02%.

Despite considerable changes in the occupation choice of natives, the effect of immigration on the average earnings would have been negligible with a less than 1% change in every occupation. In particular, the average earnings of natives would have increased only by 0.05% in engineering and by 0.51% in medical occupations. In contrast, the average earnings would have decreased by 0.18% for native managers and by 0.14% for native "other" professionals. Because engineering and science jobs pay higher wages, and more natives would have worked in these jobs in the counterfactual economy, the average earnings of native college graduates would have been 0.24% higher after the restriction of immigration.

I comparable these estimates to a small number of papers in the literature, which also estimate the effects of immigration with counterfactual simulations from a dynamic model of education and employment choices. In the context of U.S. higher immigration, Bound et al. (2015) analyze the effects of immigration on natives' employment, earnings, and degree attainment with a focus on computer sciences. For a range of labor demand elasticities, they find that the number of native computer scientists would have increased by 7.0% to 13.6%, and their average earnings would have been 2.8% to 3.8% higher if U.S. firms were not able to increase the employment of foreign computer scientists above its 1994 level. My estimate for the effect on native engineering employment (8.1%) is in the range of estimates in Bound et al., but they find more adverse effects on earnings. On the other hand, Llull (2016) finds that the earnings of white-collar workers would have increased by 0.09% if the population of both low-skilled and high-skilled immigrants were reduced to its 1965 level. This result is more in line with my estimate of a 0.24% increase in the average earnings of native college graduates.

Table 13: Percentage Change in Native's Outcomes

	Business	Engineering	Science	Other	All
Labor Market Outcomes					
Employment	-0.60	8.09	6.84	-2.87	0.02
Earnings	-0.18	0.05	0.51	-0.14	0.24
Skill Prices	-0.02	0.31	0.28	-0.29	0.07
Degree Attainment					
Bachelor's	-1.17	6.10	4.44	-2.14	0
Master's	-1.81	8.10	5.07	-3.47	-0.91
Doctorate/Professional	-3.87	5.55	8.83	-5.06	-0.11

Note: The table compares natives' average outcomes in the baseline and counterfactual economy. I assume that the unit rental price of capital and the wage of low-skilled workers stay the same at their values observed in the data. A more detailed description of the assumptions in the counterfactual simulations can be found in the main text.

The estimated effects on earnings might be driven by changes in two margins: the skill composition of workers and the unit skill prices. The third row of Table 13 displays changes in the average of the skill prices in each occupation. In a similar direction of the change in earnings, the average of the unit prices of engineering and science skills would have increased respectively by 0.31% and 0.28%. On the other hand, the average price of managerial and "other" skills would have decreased respectively by 0.02% and 0.29%. These results suggest that foreign scientists and engineers boost the productivity of natives working in the rest of the occupations. Thus, the restriction of immigration would result in earnings losses for natives in complementary occupations. Peri and Sparber (2011) and Hunt (2012) show that natives move to managerial jobs in which they can use their comparative advantage in communication and language skills in response to the influx of foreign scientists and engineers. In this paper, I provide an underlying mechanism for this finding by allowing a complementarity between different types of high-skilled workers in the aggregate production function. As a result of this complementarity, I find that the productivity in managerial and "other" jobs (as reflected on the unit skill prices) would have decreased after restricting the entry of immigrants who are more prevalent in science and engineering fields.

Degree Attainment: The bottom panel of Table 13 presents the percentage change in the proportion of natives holding each post-secondary degree type compared to the baseline economy. Similar to the change in the occupation concentration, natives would have become more likely to major in science and engineering at each level of study. In particular, the results show that the number of native engineering majors would have been 6.1% higher, and native science majors would have grown by 4.4% after the restriction of immigration. Since I do not model the external margin of college enrollment, the increase in the number of science and engineering majors implies a decrease in at least one of the remaining fields. The results show that the number of natives majoring in business and "other" fields would have declined respectively by 1.1% and 2.4%.

The effects on natives' attainment of advanced degrees follow a similar pattern to the effects estimated for the bachelor's majors. Natives would have been more likely to hold science and engineering advanced degrees and less likely to hold ones in business and "other" fields. For instance, the number of native master's degree holders would have increased by 8.1% in engineering and 5.0% in science fields, which are slightly larger than those found at the bachelor's level. Because of the decrease in the advanced degree attainment in business and "other" fields, the total number of natives with a master's degree would have decreased by 0.91% and those with a doctorate/professional degree would have declined by 0.11%.

B. The Heterogeneity in the Effects of Immigration

Table 14 presents the percentage change in natives' labor market outcomes and bachelor's degree attainment in each decade since 1960. Because the population of immigrant cohorts arriving after the 1990s is larger compared to previous cohorts, the effects of immigrants are expected to be larger for natives choosing a college major and occupation during the post-1990 period. The results in Table 14 are consistent with that expectation. For instance, the number of native engineers during the 2000s would have increased by 11.8%, while it would have been only 3.1% higher during the 1970s.

Similarly, natives of recent cohorts would have been more likely to major in engineering and science fields compared to previous cohorts. In particular, the number of engineering majors would have been 9.2% higher for cohorts born during the 1980s (i.e., those graduated from college during the early 2000s). Despite these considerable changes in employment and degree attainment of recent cohorts, the average earnings would not be different too much in any decade since 1960 because of the balancing role of adjustments in natives' labor supply as discussed in more detail in next section.

Table 14: The Heterogeneity in the Effects of Immigration

Years:	**1960-69**	**1970-79**	**1980-89**	**1990-99**	**2000-09**
Employment					
Business	-0.2	-0.4	-0.7	-0.8	-0.8
Engineering	1.0	3.1	6.1	9.0	11.8
Health	3.4	6.1	7.1	7.9	7.9
Other	-0.5	-1.3	-2.2	-3.3	-4.4
Earnings					
Business	0.0	-0.1	-0.1	-0.2	-0.3
Engineering	0.0	-0.1	0.0	-0.1	0.1
Health	0.1	0.2	0.5	0.6	0.7
Other	-0.1	-0.1	-0.1	-0.1	-0.2
Cohorts Born in:	**1940-49**	**1950-59**	**1960-69**	**1970-79**	**1980-85**
Bachelor's Fields					
Business	-0.6	-1.0	-1.4	-1.7	-1.3
Engineering	2.1	4.0	6.9	9.5	9.2
Health	4.1	4.7	5.1	5.0	4.2
Other	-1.0	-1.5	-2.4	-3.2	-3.5

Note: The table compares natives' average outcomes in the baseline and counterfactual economy in each decade since 1960. See Table 13 for the assumptions in the counterfactual simulations.

C. The Role of Equilibrium

The finding that the average earnings would not differ noticeably in the counterfactual economy suggests that adjustments in natives' behavior mitigate potential gains in earnings. The mechanism behind this finding can be described as follows. Since immigrants are more prevalent in science and engineering fields, the restriction of immigration decreases the supply of skills particularly in these fields. This decrease initially makes the marginal productivity of engineering and science skills higher, and it increases earnings in these occupations. In response, more natives study for degrees in engineering and science fields and work in related occupations. The fact that more natives move to science and engineering fields in the absence of immigrants pushes the associated skill prices back to the levels similar to ones found in the baseline economy such that potential wage gains are largely offset. Thus, estimating the effects of immigration without considering the balancing role of adjustments in natives' education and labor supply behavior might be biased.

To quantify the potential bias, I simulate the average earnings in a counterfactual economy where I restrict the immigrant population to its 1960 level and do not allow natives and remaining immigrants to adjust their behavior. In particular, I keep the probability of choosing employment and degree alternatives constant as found in the baseline economy and calculate the unit skill price of each high-skilled labor type from its marginal productivity condition. This analysis shows that the earnings of native college graduates would have increased by 1.5% on average, and they would have grown by 0.5% for managers, 11.1% for engineers, and 9.1% for scientists, but they would have decreased by 2.4% for "other" professional workers.[46] In contrast, I find only a 0.24% increase in the average earnings, allowing adjustments in education and employment behavior as discussed before. This finding suggests that the adverse effect of immigration on earnings is overestimated if the balancing role of adjustments in natives' labor supply is ignored.

D. Total Employment in Science and Engineering

Although natives' likelihood to pursue science and engineering careers would increase after the restriction of immigration, it might not be enough to maintain the level of the proportion of scientists and engineers which is found in the baseline economy. Table 15 shows the percentage change in the proportion of people employed in each

[46] These figures are comparable to the previous literature that analyzes the effects of all immigrants including low-skill workers without considering the adjustments in the labor supply behavior of natives. For instance, in case of full capital adjustment as assumed in this paper, Ottoviano and Peri (2012) find that immigration has an effect on native wages from -0.1% to +0.6% in the period from 1990 to 2006. On the other hand, in case of no capital adjustment, Borjas (2003) finds the elasticity of average earnings with respect to the percentage change in the labor supply induced by immigration around -0.3. My estimates imply the elasticity to be -0.13 (i.e., the 1.5% increase on earnings divided by the 11.2 percentage point increase in the share of immigrants as observed in the data from 1960 to 2010).

occupation, the average earnings, and the proportion of people holding each degree type for the combined sample of native and immigrant college graduates. Because immigrants are more likely to work and earn higher wages than natives, the decrease in their population in the counterfactual economy would have reduced the proportion of all college graduates employed in each occupation. Also, the average earnings would have decreased in the range of 1.23% in management to 1.43% in science jobs. More noticeably, the proportion of college graduates with the engineering bachelor's degree would have dropped by 12.9%, and the proportion of those with the engineering doctorate degree would have dropped by 20.6%. Because natives with other degree types become more likely to work in engineering in the counterfactual economy, the proportion of people working in engineering would have been similar to the level observed in the baseline economy with only a 1.45% decline.

Table 15: Percentage Change in All College Graduates' Outcomes

	Business	Engineering	Science	Other	All
Labor Market Outcomes					
Employment	-1.14	-1.45	-1.43	-0.02	-0.78
Earnings	-1.23	-1.39	-1.43	-1.24	-1.36
Degree Attainment					
Bachelor's	-1.1	-12.9	-1.0	4.5	0.0
Master's	-5.5	-14.9	-0.2	2.3	-2.1
Doctorate/Professional	-0.76	-20.60	-5.72	-1.41	-5.05

Note: The table compares the average outcomes in the baseline and counterfactual economy for the sample of all college graduates, including natives and immigrants. See Table 13 for the assumptions in the counterfactual simulations. The results for employment present the percentage change in the proportion of people employed in each occupation. The results for degree attainment present the percentage change in the proportion of people holding each degree type. The results for earnings present the percentage change in average earnings.

This decline in the proportion of engineering degree holders might generate some unintended consequences that cannot be captured with the structure of the current model. In particular, the model weights the labor supply of workers with the efficiency units (i.e., skill units), and it does not impose a different elasticity of substitution across holders of different degrees. For instance, if a worker with an engineering doctorate degree has two units of engineering skills, and a worker with an engineering bachelor's degree has one unit; then the model assumes that two bachelor's degree holders can be perfectly substitute of one doctorate degree holder. For some jobs, such as professorship, this assumption seems not reasonable. Thus, the estimated 20.6% decline in the proportion of doctorate degree holders in engineering might generate large negative effects in the production of particular industries, such as universities and colleges. Moreover, the total number of engineers might be a determinant of innovation. Thus, the decline in their population might cause some negative spillover effects on earnings of every worker in the economy. Thus, the estimated effects in this study might be considered as the upper bound for the effects of immigration on earnings.

VIII. Conclusion

In this paper, I build a dynamic discrete choice model to analyze the effects of high-skilled immigrants on natives' post-secondary degree attainment and labor market outcomes. Unlike the existing literature, I allow earnings to be determined as an outcome of the market-clearing process. I estimate the model for the U.S. economy with data from several sources. I use the estimates to simulate a counterfactual economy where the entry of high-skilled immigrants is restricted after 1960. I find that the number of natives holding engineering and science degrees would have increased at each level of study. Consequently, the number of native engineers and scientists would have increased in the labor market. However, the average earnings of natives would not increase noticeably in engineering and science jobs, and they would even slightly decrease in managerial and "other" professions. These findings suggest the importance of considering the equilibrium in an analysis of immigration because the equilibrium mechanism would offset the potential increases in earnings as more natives move to the areas that are protected from immigrants.

In sum, the concern that high-skilled immigrants discourage native students from pursuing science and engineering careers is partially supported in this study as I find that the number of natives with science and engineering degrees would be higher without the last five decades of immigration. However, the concern that immigrants harm the earnings of natives is not supported because adjustments in natives' labor supply behavior would mitigate the potential gains. Moreover, the restriction of immigration might generate some unintended consequences because of complementarities in the production technology. I find a slight decrease in the earnings of native workers in management and "other" professions. Last but not least, the total number of engineers with a doctorate degree would decline significantly after the restriction of immigration. Such a decrease in the supply of qualified workforce might be harmful for U.S. innovation and productivity which should be analyzed in future research.

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Chapter 2

International STEM Students and the US Labor Market: The Role of Visa Policy[1,2]

I. Introduction

International students represent an increasing share of enrollment in U.S. higher education, particularly at the bachelor's and the master's levels. Moreover, the international student population is particularly prevalent in science, technology, engineering, and mathematics (STEM) fields.[3] Yet, international graduates of U.S. colleges and universities have few opportunities to stay in the United States unless an employer sponsors them for a work visa, a costly and uncertain process. Difficulties in obtaining permission to work in the United States may encourage talented international students to accept job offers from firms in other countries. Some policy makers have proposed altering visa policy to make it easier to retain this U.S.-educated STEM workforce.[4] Proponents of these bills highlight the importance of STEM majors as a boost to innovation and growth, yet increases in the supply of foreign STEM graduates might concurrently harm employment opportunities for native STEM graduates.

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[2] This research was supported by a grant from the American Educational Research Association which receives funds for its "AERA Grants Program" from the National Science Foundation under Grant #DRL-0941014. Opinions reflect those of the author and do not necessarily reflect those of the granting agencies. The use of NSF data does not imply NSF endorsement of the research methods or conclusions contained in this report.

[3] The share of international students among graduates of U.S. colleges and universities increased from 3.0 percent in 2006 to 3.6 percent in 2013 at the bachelor's level and from 12.0 percent to 13.1 percent at the master's level (author's tabulations from the IPEDS Completion Surveys). As of 2013, international students obtained about 7 percent of STEM bachelor's degrees and 42 percent of STEM master's degrees granted by U.S. colleges and universities, but only 3 percent and 10 percent of degrees in other fields at each level, respectively. See Figure A1 in the appendix for the evolution of the population and share of international students over the last three decades by the field and level of study.

[4] For example, the SKILLS Visa Act of 2013 (H.R. 2131) proposes to allocate up to 55,000 permanent residency cards to STEM graduates of U.S. universities and colleges at the master's and doctoral level, while the 2013 Border Security, Economic Opportunity, and Immigration Modernization Act (S. 744) proposes no cap for STEM doctorates and allocates up to 40 percent of permanent residency cards for STEM master's degree holders.

The Optional Practical Training (OPT) program provides a critical bridge for international students to access the U.S. labor market because it extends student visas for 12 months, allowing them to gain work experience in U.S. firms after graduation without holding a formal work visa. Because the H-1B visa— the most common type of temporary work visa for highly skilled immigrants— requires time-intensive and costly employer sponsorship with restrictive quotas, OPT generates easier access to the U.S. labor market. As a result, many international students use OPT to start working in the United States. For instance, over the last decade, 72 percent of international graduates of bachelor's- and advanced-level programs stayed in the United States after graduation, with 83 percent of stayers using OPT for at least six months and 67 percent doing so for 12 months. Students at the master's level are even more likely to use OPT, with 76 percent of them initially staying via OPT, with 85 percent of stayers using it for at least six months and 69 percent using it for at least 12 months (SEVIS data, see Section III).

In 2008, the U.S. government extended OPT work permission from 12 to 29 months for degree recipients in most STEM fields. I employ this unique variation in the program to address two fundamental questions: (i) whether and to what extend extended visa terms affect the participation of international students in the U.S. labor market, and (ii) how an increase in the supply of foreign students to the U.S. labor market affects the employment and earnings of native peers. Understanding the impact of the OPT extension may provide insight into the degree at which the current H-1B cap restrains foreign students' access to the U.S. labor market, which would be helpful in assessing the possible effects of recently proposed changes in visa policy for high-skill workers.

To address these research questions, I use administrative data from the U.S. government obtained through a Freedom of Information Act (FOIA) request. This new data set provides unique evidence on the post-graduation experiences of international students, along with their educational records. I observe several measures of post-graduation participation in the U.S. labor market, including whether students continued to stay in the U.S. after graduation and how long they stayed using OPT. I refer to these measures of post-graduation outcomes in the United States as “persistence” throughout this paper.

I adopt a difference-in-differences (DD) strategy to estimate the effect of the OPT extension on the persistence of international students in eligible fields. International students in non-eligible fields serve as a control for patterns in the labor supply of eligible STEM students in the absence of the OPT extension. I find that extended visa terms increase international STEM students’ entry into the U.S. labor market and lengthen their employment spell. I also find that the extension affects the persistence of students differently across levels of study. I interpret longer employment spells as evidence that students’ access might be “constrained” in the U.S. labor market owing to the H-1B cap. Meanwhile, the estimated increase in the likelihood of initially staying suggests that the OPT extension might enhance the “option value” of employment, during which firms and former students evaluate match quality before engaging in a longer and more costly job contract.

In particular, I find the largest estimates at the master’s level, indicating a 6.2 percentage point increase in the likelihood of staying and a 153-day extension in employment spells. On the other hand, the likelihood of staying increases by 3.6 and 2.1 percentage points at the bachelor’s and doctorate levels, respectively, and the employment spells increase by 96 and 90 days. The results show that the OPT extension increases the number of STEM labor-days supplied by foreign master’s-level workers to the US economy by about half. The findings imply that the H1-B cap largely restricts the employment of foreign workers with master’s degrees. Because doctorates might work in academic and nonprofit research institutions that are exempt from the H-1B cap, the OPT extension does not affect their persistence at the levels it does for master’s students.

A concern is that the Great Recession might undermine the parallel trends assumption between the persistence in eligible and non-eligible fields. Yet the results are robust after I include controls for labor market conditions, such as local unemployment rates, field-specific GDP, and labor demand for foreign workers. As another robustness check, I estimate a different DD model in which I use students from countries with alternative work visas as a control group, restricting the sample to students only in eligible fields. I find that the extension increases the persistence of students without alternative visas more than students with alternative visas, which alleviates concerns about unobserved labor demand conditions in eligible fields.

Next, I examine the effect of the resulting increase in the labor supply of international students to STEM fields on the employment and earnings prospects of native students. To do so, I define markets for labor skills of recent college graduates by field of study and level of degree and then examine the relationship between the percentage of workers in a skill market who are recent foreign graduates and the performance of recent native graduates in the same skill market. As more foreign students might be present in a particular labor market that has unobservable high labor demand, I use an instrumental variables (IV) approach to isolate the shift in foreign labor supply resulting from the OPT policy change.

I find that, at the master's level, a 1 percentage point increase in the share of foreign students in a field (about one-third of what was actually observed in the average STEM field) decreases current employment of recently graduated natives in the same field by 0.3 percentage points (a 4.3 percent increase in unemployment), full-year full-time employment by 0.7 percentage points (a 3.3 percent increase in full-year full-time unemployment), and annual earnings by 1.6 percent. These results suggest economically important effects of visa policy on natives' labor market outcomes, which must be balanced against the possible productivity gains arising from retaining international students in the United States. My calculations show that the observed increase in the international student share after the OPT extension seems enough to achieve the increase in earnings for natives due to productivity gains based on the estimates of patenting elasticities in the literature.

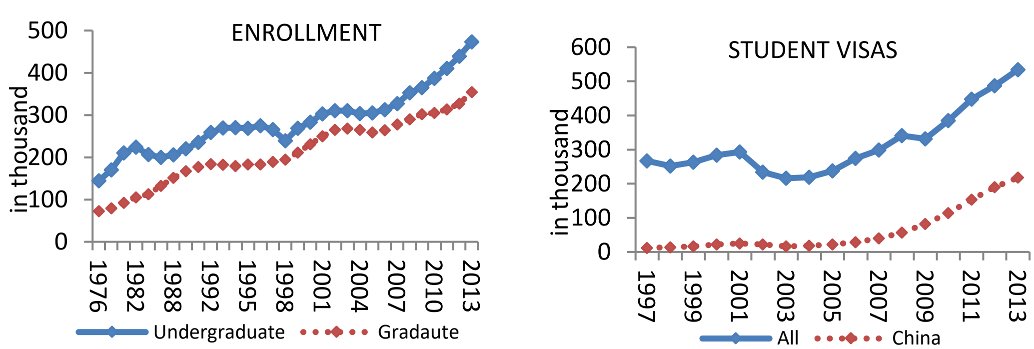
In the next section, I provide a brief overview of the relevant literature, describe current visa policy, and discuss the theoretical implications of the OPT extension. Section III introduces the unique administrative data employed in this analysis. Section IV lays out the estimation strategy and results on the persistence of international students. Section V analyzes the effect on the labor market outcomes of natives. Section VI concludes.

II. Research Background and Theoretical Framework

A. Trends in Foreign Enrollment and its Determinants

The total enrollment of international students in both undergraduate and graduate programs has grown substantially over the last three decades (Figure 1, Panel A), except for a few periods associated with contracting economic opportunities and stringent visa requirements related to national security concerns (Lowell and Khadka, 2011). Since 2006, the increase has been particularly marked, with distinctly faster growth at the undergraduate level (6.1 percent annually) than at the graduate level (4.3 percent). Moreover, changes at the graduate level have concentrated in master's programs. Based on visa statistics from the U.S. Department of State, students from China have been the driving force of this growth (Figure 1, Panel B). In 1997, Chinese students held only 4 percent of student visas; in 2013, they held 41 percent.

FIGURE 1. THE STOCK AND FLOWS OF INTERNATIONAL STUDENTS IN THE UNITED STATES



Notes: The enrollment series display the total number of enrolled students with temporary visas in undergraduate programs (only the bachelor's level) and graduate programs (combining the master's and the doctorates level). The student visas series display the total number of new F visas (the primary type of student visa) issued each year.

Source: IPEDS 1976-2013, Enrollment Surveys in Panel A; and the U.S. Department of State, Nonimmigrant Visa Issuances by Visa Class and by Nationality in Panel B.

In turn, degrees awarded to foreign students have grown at all levels, including the bachelor's, master's and doctorate programs, with their field of study particularly concentrated in STEM fields. For instance, the share of foreign students among graduates of bachelor's programs increased from 3.0 percent in 2006 to 3.6 percent in 2013, and their share in master's programs increased from 12.0 percent to 13.1 percent. Their share in STEM programs has been much higher than their share within all programs because foreign students have been more likely to major in STEM fields compared to natives. In particular, in 2013, 19.8 percent of foreign students majored in STEM fields at the bachelor's level and 35.5 percent at the master's level, whereas 9.7 percent of native students majored in STEM at the bachelor's level and 7.4 percent at the master's level. As a result, foreign students obtained 7.1 percent of STEM bachelor's degrees and 42.3 percent of STEM master's degrees granted by U.S. universities and colleges in 2013. Furthermore, the degree receipt by foreign students in STEM fields has been more cyclical than the one in non-STEM fields, with a marked increase in STEM following the IT boom of the late 1990s (Figure A1 in the appendix).

The "school-constrained" and the "migration" model are two theoretical approaches used to explain international student mobility (Rosenzweig 2006). The school-constrained model emphasizes home country supply constraints in post-secondary options as driving motives of student flows, whereas the migration model focuses on the motive to find high-paying jobs in the destination country after graduation. The empirical evidence in the U.S. context is mixed to date. Some researchers find that both the increased competition for college enrollment in home countries and the increased ability to pay U.S. tuition raise demand for U.S. education (e.g., Hwang, 2009, and Bird and Turner, 2014). Other studies find that foreign students' enrollment responds to changing job prospects in the U.S. labor market, proxied by variations in visa caps or demand shocks in specific industries (e.g., Kato and Sparber 2013, Shih 2016, and Bound et al. 2014). Although the latter studies provide some evidence for the migration motive, the principal tenant of this model is that foreign students enroll in U.S. schools in order to obtain U.S. employment. Whether and at what levels foreign students transition to the

U.S. labor market is noticeably absent in the literature up to this point, with the exception of a few studies at the doctoral level.[5] This study provides evidence of this missing piece by using a new administrative data set in the context of a unique policy variation, which I describe in the following section in detail.

B. Student Visas and the Optional Practical Training (OPT) Program

There are three types of student visas: M visas for vocational study, J visas for cultural exchange programs, and F visas for academic study. Among them, F visas are the most prevalent type as 94 percent of universities sponsor their foreign students under the F visa program (SEVP, 2014). Because there is no cap on the number of student visas that can be issued per year, the capacity to finance and academic preparedness compose the two main conditions to be eligible for an F visa, particularly at the bachelor's and master's level, while doctoral students generally get stipends. Upon graduation, F visas provide a limited period during which these now former students may work at U.S. firms before they must be sponsored via another type of work authorization. This period is known as Optional Practical Training (OPT).[6]

The value of the post-graduation employment opportunity via OPT becomes more apparent when it is compared with other entry channels to the U.S. labor market. H-1B visas are the most popular program for the employment of college-educated foreign workers, as they provide work permission for up to three years with the potential for a three-year extension.[7] However, the number of H-1B visas is subject to a restrictive cap

[5] The Survey of Earned Doctorates collects data from graduates of U.S. doctoral programs. While Bound et al. (2009) and Blanchard et al. (2009) explore factors affecting the growth of international students with data from this survey, Grogger and Hanson (2013) employ the question about the intention of international students to stay in the United States after graduation and find that their ties to the United States and academic ability are positively related to their intention to stay. Finally, Finn (2014) merges this survey with administrative tax data and presents high levels of persistence with 68 percent of international PhD recipients staying in the United States five years after graduation, 65 percent staying 10 years and 61 percent staying 16 years afterward.

[6] In addition, F-visa students may work part-time up to 20 hours even during schooling, which is known as Curricular Practical Training (CPT). Yet, the time employed on CPT counts toward the total limit in the OPT period, and only 1 percent of students use CPT (Wasem, 2012).

[7] There are a few other visa opportunities for college-educated foreign workers: permanent visas and L visas. However, the cap on employment-based permanent visas has been restrictive and only 3.3 percent of those visas were issued to students in 2001 as of the most recent year when these statistics were released (U.S. Immigration and Naturalization Service, 2002). L visas are not feasible for most international students, as they require work experience abroad in the prior year to application.

at 65,000 per year. The employees of universities and other nonprofit research institutions are exempt from the quota. This rule makes holders of doctorate degrees less likely to be bound by the H-1B cap as they have an option to work in the exempt institutions (Amuedo-Dorantes and Furtado 2016).

The number of applications has exceeded the cap each year since 2004. Although Congress introduced an extra 20,000 H-1B visas per year in 2005 for workers holding advanced degrees from U.S. universities and colleges, this extended cap has been binding each year since its inception (Table A1). Indeed, a simple comparison of the total flows of international graduates to the H-1B cap suggests that not every U.S.-educated student can be sponsored under the H-1B program even if U.S. firms are willing to hire them.[8]

In sum, the transition to the U.S. labor market with student visas (via OPT) after post-secondary study provides a window of opportunity to obtain long-term employment in US firms. In 2008, the U.S. government extended the OPT term from 12 to 29 months for graduates of most STEM fields. As a result, international graduates in computer sciences and mathematics, engineering, and biological and physical sciences became eligible to stay in the United States up to 29 months after graduation by holding their student visa status.[9] In 2011 and 2012, eligibility was further expanded to students in pharmaceutical, agricultural and environmental sciences (see the appendix for further discussion of fields).

[8] In recent years, about 15,000 international students at the doctoral level and 60,000 at the master's level graduate from U.S. colleges and universities per year (see Figure A1). Thus, the allocated 20,000 visas for advanced degree holders are significantly less than the flow of new graduates. Although the rest of the advanced degree holders might be subject to regular quota of 65,000 visas, this process is quite competitive because an additional 50,000 new graduates at the bachelor's level and immigrants from abroad might apply for these visas.

[9] All students with a degree in eligible STEM fields can use the 17-month extension after completing the initial 12 months of their OPT. Although the law requires employers to register on the E-verify system, which is a federal system designated to check employee's eligibility to work legally in the United States, firms can easily enroll to the system online and there is no evidence for firms' hiring decision affected by the E-verify requirement, with the exceptions for immigrants who are likely to be unauthorized (Amuedo-Dorantes and Bosnak 2012, Bohn et al. 2014, and Orrenius and Zavodny 2014). Moreover, the 2008 regulations set the unemployment limit at 120 days for those on the OPT extension period, while it was kept at 90 days for all other students. Also, student visas of those with a properly filed and approved H-1B petition were automatically extended up to six months, regardless of the field of study.

C. Potential Consequences of the OPT Extension

The sign of the effects of the extension of OPT duration is positive, with potentially more students persisting in the United States and some students extending their stays. Yet, the overall magnitude of the impact of this visa extension on the supply of STEM workers is an empirical question. In the context of the OPT extension, this increase might be realized under three channels. First, international students who complete the initial 12 months of their OPT but are unable to transfer to an H-1B visa, can continue in their current employment up to 29 months after the OPT extension. To the extent that the foreign graduates' ability to work in the U.S. labor market is limited by the H-1B cap, the OPT extension might generate longer employment spells on student visas, particularly beyond 12 months.

Second, the value of the initial employment and, as a result, the likelihood of initially staying in the United States might increase with the OPT extension. Such an effect might be realized because the OPT extension provides a longer job contract without being subject to the uncertainty of obtaining an H-1B visa. These longer payoff streams would be more likely to compensate fixed costs of employment, such as job-related training for firms and moving expenses for students. Moreover, college students graduating in May used to have only one chance to apply for an H-1B visa (about 10 to 11 months after graduation) because H-1B permits have usually been exhausted in the first week of April. With the OPT extension, students in eligible STEM fields get two chances to apply (once after 10 to 11 months and again 22 to 23 months after graduation if the first attempt fails). This reduced uncertainty of obtaining an H-1B visa might further increase firms' likelihood of hiring foreign students.

Third, students and firms might use the OPT term as a screening period to learn the true match quality. Thus, an employer might reassess the sponsorship decision for the H-1B visa based on new information learned during the OPT extension. The theory suggests that the option value of reassessment in decisions with uncertain payoffs increases the realization of risky behaviors, such as the dropout option increasing the value of college attendance (Stange, 2012, Eisenhauer et al. 2015, and Lee et al. 2015).

The magnitude of the effect may vary across different groups of students. The labor supply of foreign students who are more likely to be restricted by the H-1B cap should increase more with the OPT extension. Thus, the persistence of students at each level of study and type of universities might be affected differently depending on the restrictiveness of the H-1B cap for each group. Moreover, students from less-wealthy nations might respond more to the OPT extension due to a substantial wage premium relative to their home country, strengthening their incentive to stay in the United States. To explore such heterogeneity, I will examine whether country of origin, level of study, or quality of the university attended influences the impact of the OPT extension.

D. Impact of Foreign-born Workers on Natives in the Labor Market

Increases in the supply of foreign workers might affect labor market outcomes of natives. To the extent that foreign workers substitute closely for natives, an increase in the foreign labor supply would lead to a deterioration of natives' employment and earnings, while the magnitude of impact depends on the elasticity of labor demand. A more inelastic demand schedule corresponds to a larger decrease in natives' earnings. In contrast, if the demand elasticity is high due to factors such as agglomeration effects and the potential of off-shoring in the context of STEM occupations (Bound et al., 2013), then there may be negligible effects on native employment and earnings.

Previous studies explore the link between variation in high-skill immigration to local markets and native employment and earnings in those areas. As an instrument for an exogenous increase in the labor supply, most studies use the interaction of the national level variation in high-skill immigration, usually driven by changes in the H-1B cap, with the dependency of local markets on immigrants (e.g., Kerr and Lincoln 2010, Peri et al. 2014, and Kerr et al. 2014). They find that highly-skilled immigrants do not crowd out native employment and have negligible effects on natives' earnings.[10] However, to the extent that agglomeration effects cause a concentration of STEM industries in particular regions and the expansion in the H-1B cap was driven by a strong labor demand of the late 1990s in those same regions, the instrument based on local dependencies would be endogenous. Bound et al. (2015) model both education and employment choices in a structural framework where markets for labor skills are defined by field of study, and they find some adverse effects on natives' outcomes.

My work differs by focusing on the impact of international graduates of U.S. universities rather than all foreign workers and by exploiting a unique policy variation that changes the foreign labor supply across fields rather than geographic areas. Because U.S. education might make international students more accustomed to U.S. business culture and more fluent in the English language, U.S.-educated foreign workers may be closer substitutes for natives, and this might generate more adverse effects in natives' labor market performance. Indeed, immigrants with a U.S. degree earn more than immigrants with a foreign degree at the same level of education (Hunt 2011, and Bound et al. 2014), which highlights heterogeneity across immigrants' skills with respect to the location of their education.

III. Data

A. Administrative Data Source for International Students: SEVIS

In order to estimate the impact of the OPT policy change on the participation of international students in the U.S. labor market, I need data of degree completion by field of study along with post-graduation placement. I obtained administrative data from the Student and Exchange Visitor Information System (SEVIS) through a FOIA request.[11]

[10] Researchers focusing on the labor market for doctorates find that international doctorate students dampen native earnings and push natives to accept post-doc positions or concentrate on subjects that immigrants are not studying (e.g., Borjas 2009, Borjas and Doran 2012, and Lan 2013). See Kerr (2013) for the survey of this literature.

[11] Since August of 2003, the Department of Homeland Security (DHS) requires all schools to report the information of their foreign students for the sake of national security and SEVIS is created in response to this mandate (Haddal, 2006)

The data set is an individual-level census of F-visa students who either adjusted to another visa or departed the United States any time between January 1, 2004, and June 26, 2014. I observe exact dates of when a student started and completed post-secondary study along with when her F-visa status terminated. In terms of educational records, I observe the intended degree, field of study, and the name of the institution attended. As such, I can identify whether the student was eligible for the OPT extension by virtue of the field and the date of school completion. Finally, I observe some demographic characteristics of students, including country of origin, year of birth, and gender, as well as several measures of post-graduation persistence in the United States.

The length of the period between college completion and F-visa status termination provides some insights about post-graduation residency. The law requires students either to transfer to another visa or to apply for OPT within 60 days after graduation. Visas of students who have not taken either action are revoked at the end of this "grace period." Indeed, the date of F-visa status termination is exactly 60 days after college completion for about one-third of all students in the data. Therefore, I identify those observations as the students who left the country right after graduation without entering the U.S. labor market. In addition to this measure of "initial" post-degree persistence, I also calculate the length of the employment period on OPT as the difference between the dates of school completion and F-visa status termination.

Nonetheless, the available SEVIS administrative data have some limitations. First, I do not observe visa status after F-visa status completion. Once the student visa expires, a student might leave the country or continue to stay by transferring to another visa, including an H-1B visa, an employment-based permanent visa, or a family-related visa by marrying a native or permanent resident. Therefore, I cannot explore whether and how the OPT extension affects the likelihood of long-term residency in the United States. Second, I do not know whether a student actually obtains the degree pursued or drops out of the program. Indeed, for some of the observations, the period between the school start and completion dates does not seem long enough to obtain the degree pursued. I include these students in the empirical analysis below, as they might still stay in the United States via other channels. Yet I also show that the results are not sensitive to these students' inclusion (Table A2). Third, the data do not have a longitudinal feature. For instance, if a student obtains a bachelor's degree in May from a U.S. institution and then starts a doctorate program in August in the United States, I observe these actions as separate entries without any person specific identifier.

B. Sample Statistics of International Students in SEVIS

I restrict the sample to those who completed study between January 1, 2004, and June 30, 2011, so that every student in the sample should have run out his or her F-visa status as of the last day observed in the data (June 26, 2014). In addition, I drop those who adjusted their visa status before completing their schooling (about 5 percent), as they likely obtained a family-related visa.

Table 1 reports summary statistics by level of study and eligibility status of fields for the OPT extension. Students in the eligible STEM fields are more likely to be male and slightly younger than are students in non-eligible fields at all degree levels. The predominance of Indian students in eligible fields at the master's level (60 percent of all the students in master's programs) and Chinese students at the doctorate level (35 percent) is also noteworthy. In addition, there is a marked concentration of international students in colleges and universities with high research activity, regardless of the field and level.

In terms of the persistence measures of interest, the percentage of students who stay in the United States after completion of study is 72 percent on average and even higher for students in fields that are eligible for the OPT extension. For instance, 89 percent of students in eligible fields at the master's level stay, slightly higher than at the doctorate level. Conditional on initially staying after college, the average length of stay on student visas is close to 12 months and is higher at the master's and bachelor's levels than at the doctorate level, perhaps because doctoral students convert to other types of work visas sooner.

TABLE 1: SUMMARY STATISTICS, INTERNATIONAL STUDENTS, SEVIS DATA

	Bachelor's		Master's		Doctorates	
Eligibility for the OPT extension:	Eligible Fields	Non-Eligible	Eligible Fields	Non-Eligible	Eligible Fields	Non-Eligible
Number of Observations	51,667	181,408	145,672	238,198	67,391	42,254
% Female	31.6	55.1	28.8	51.5	28.3	48.8
Mean Age (at school completion)	23.8	24.1	25.7	28.9	30.9	33.2
% China	3.3	3.6	11.4	12.8	35.9	14.9
% India	9.6	3.5	60.6	13.1	17.4	8.2
% Korea	8.7	10.9	2.8	8.5	10.0	15.1
% Research University	43.9	30.4	49.5	46.4	73.2	65.4
% Comprehensive/Master's Uni.	22.7	26.7	20.8	20.3	1.4	4.3
% Computer Sciences	28.7	-	35.4	-	14.8	-
% Engineering	41.9	-	54.0	-	42.6	-
% Physical and Biological Sciences	21.0	-	6.7	-	38.3	-
% Management	-	40.7	-	47.6	-	7.9
% Stayed Initially in the United States	66.1	62.0	88.5	68.1	85.3	63.6
% Stayed 12 months via OPT	46.1	42.9	58.0	48.4	50.1	37.1
Length of Stay via OPT (in days), conditional on staying	414	366	463	384	379	336

Notes: The statistics are based on SEVIS data. The sample includes those who completed their school between January 1, 2004 and June 30, 2011. I exclude students adjusted their visa status before they completed school. The age refers to the age at school completion. The classification of universities with respect to research intensity is based on the Carnegie classification. The length of stay is measured in days only for those who initially stayed. See the online appendix for the full list of eligible fields.

IV. Impact on the Persistence of International Students

A. Research Design: Difference-in-Differences

To recover the impact on the post-graduation persistence of international students in the United States, I use a difference-in-differences (DD) approach that compares international students who are in fields that are eligible for the 17-month OPT extension after 2008 with students who are in non-eligible fields. Eligible fields consist of most STEM fields, with computer sciences and engineering majors comprising a significant share of international students in the data, whereas non-eligible fields are all non-STEM fields, with business majors comprising a large fraction of this control group (Table 1).

The key identifying assumption behind the empirical methodology is that the trends in the persistence and enrollment pattern of students in non-eligible fields proxies the pattern that would have occurred in eligible fields in the absence of the OPT extension. Although most students in the data made the enrollment decision before the extension policy was announced, a potential violation of the parallel trends assumption would arise if time-varying factors (such as the Great Recession) affect persistence in eligible fields differently than in non-eligible fields. I provide robustness checks to address this and some other concerns in Part C of this section.

Panel A in Table 2 reports the average "initial" stay rate at each level of study, and Panel B displays the average length of employment via OPT for those who "initially" stay. Columns report outcomes for students who completed study before the policy versus after, along with their difference. Rows report those outcomes separately for students in fields that are eligible versus non-eligible for the OPT extension. Figure 2 illustrates the similar statistics for each year over the sample period.

Initial stay rates fell during the post-policy period at all fields and levels. It is not surprising to observe such a drop, as the post-policy period coincided with a weak job market due to the Great Recession. Nonetheless, the decline in eligible fields was smaller relative to non-eligible fields, which results in a positive impact of the OPT extension on the initial persistence by 1.2 to 4.3 percentage points. On the other side, the average length of stay among those who initially stayed did not drop significantly in non-eligible fields, in spite of the economic slowdown, whereas it even rose in eligible fields. As a result, the relative length of stay for those in eligible fields rose by 49 to 138 days.

TABLE 2: THE IMPACT OF THE OPT EXTENSION ON INTERNATIONAL STUDENTS, DIFFERENCE IN DIFFERENCES (DD), UNCONDITIONAL ON COVARIATES

Panel A: Average Initial Stay Rate

		Before	After	Difference
Bachelor's	Non-eligible fields	0.655	0.574	-0.082
	Eligible fields	0.685	0.624	-0.061
	DD result			**0.020**
Master's	Non-eligible fields	0.685	0.662	-0.023
	Eligible fields	0.882	0.902	0.020
	DD result			**0.043**
Doctorates	Non-eligible fields	0.622	0.602	-0.020
	Eligible fields	0.8560	0.852	-0.008
	DD result			**0.012**

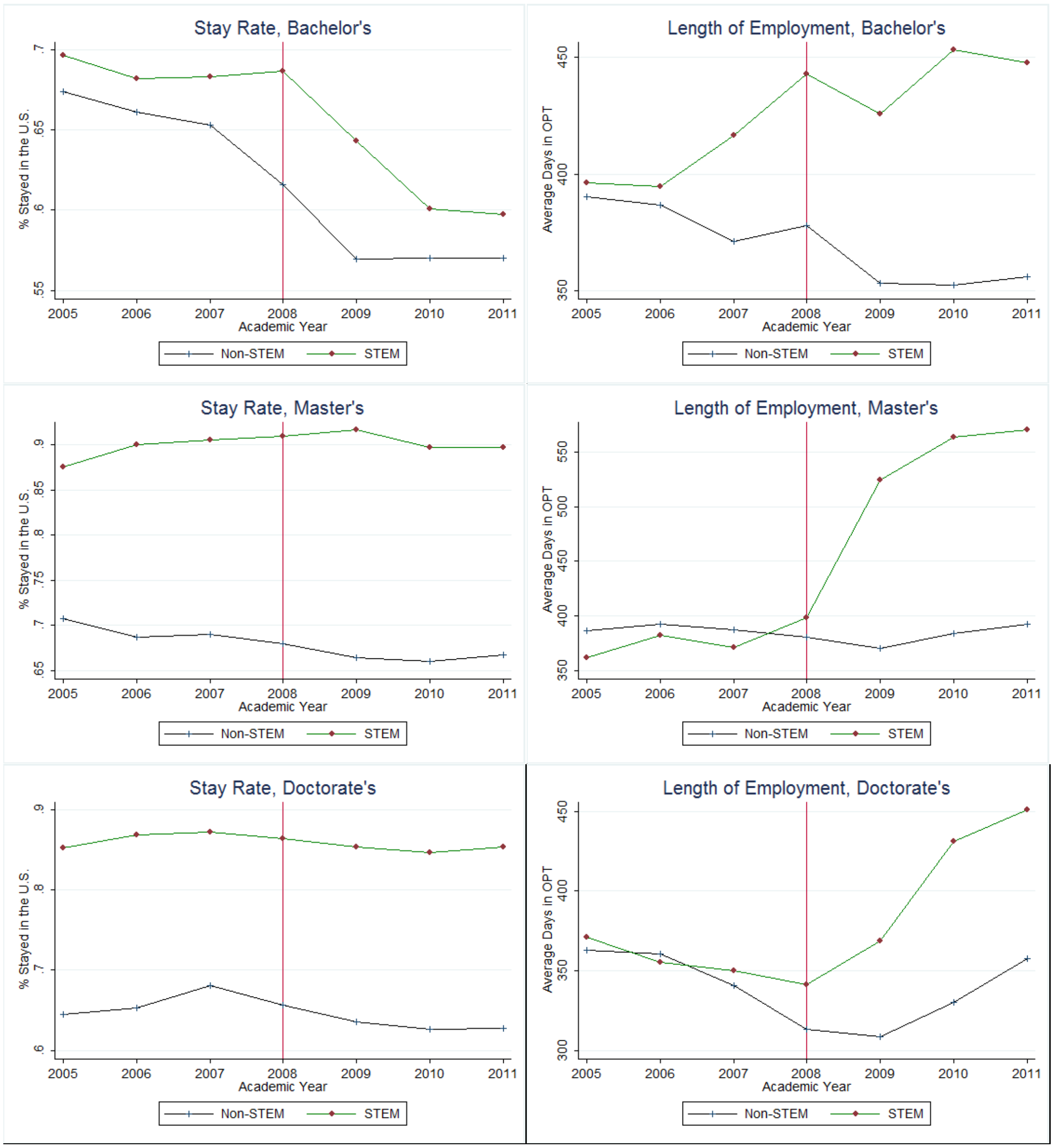
Panel B: Average Length of Stay on OPT after Graduation (in days, conditional on staying)

		Before	After	Difference
Bachelor's	Non-eligible fields	362	374	12
	Eligible fields	383	452	68
	DD result			**56**
Master's	Non-eligible fields	371	391	20
	Eligible fields	363	522	159
	DD result			**138**
Doctorates	Non-eligible fields	329	336	7
	Eligible fields	348	404	56
	DD result			**49**

Notes: "After" refers to the period after the OPT extension takes effect (i.e., students who graduated after April 8, 2008 or those who were currently on the student visa status in April 8, 2008 but having graduated in last 60 days before the extension in Panel A or in last 12 months in Panel B), whereas the "Before" period refers to all other cases. Fields are divided in terms of their eligibility for the OPT extension

Source: SEVIS data.

FIGURE 2: THE PERSISTENCE OF INTERNATIONAL STUDENTS, BY FIELD AND LEVEL



Notes: Stay rate graphs display the fraction of each class who initially stayed in the United States upon school completion. The length of stay is measured in days, conditioned on staying at all. The vertical line shows the year when the OPT extension policy was enacted.

Source: SEVIS data.

Regression analysis provides a way to address concerns about possible compositional changes in the characteristics of international students over the sample period, such as country of origin and type of intuitions attended. Let i index individuals in the group of students who completed post-secondary study in field f of school s at time t. I estimate the difference-in-differences linear model

$$(1) \qquad Y_{i_{fst}} = \beta_0 + \beta_1 OPT_{ft} + \beta_2 X_{i_{fst}} + \delta_f + \delta_t + \delta_s + \epsilon_{i_{fst}}$$

where $Y_{i_{fst}}$ represents either a dichotomous stay measure for individual i of field f and school s with completion time t or the number of days that the student stays in the United States via OPT.

The key independent variable OPT_{ft} is a binary indicator of eligibility for the OPT extension after the extension takes effect.[12] Field fixed effects, δ_f, control for permanent differences across fields, such as the high prevalence of foreign workers in computer-related occupations. Time fixed effects associated with the timing of school completion, δ_t, control for the impact of events common across all fields, such as recessions. In addition, I use school fixed effects, δ_s, to control for the possibility that graduates of some colleges might have consistently high or low stay rates, perhaps because of the colleges' quality or proximity to business areas. Finally, I capture the effect of demographic characteristics with $X_{i_{fst}}$ that includes the student i's age at school completion, gender, and country of origin.

B. Baseline Regression Results

Table 3 presents the key regression results. Each cell reports the coefficient estimate for the variable OPT_{ft} along with the robust standard errors clustered at the field and year level. The coefficients in columns (1)–(3) measure the marginal increase in the initial

[12] The policy took effect on April 8, 2008, whereas a few fields became eligible on May 11, 2011 and May 12, 2012. I count students of eligible fields who completed school in the prior 60 days before the policy took effect but were holding student visa status by the policy announced as treated, because they could apply for OPT during this "grace" period.

persistence of eligible students once the OPT extension became available, and the coefficients in columns (4)–(6) present the marginal increase in the employment spell in OPT status for those who stayed.

TABLE 3: BASELINE RESULTS ON THE PERSISTENCY OF FOREIGN STUDENTS, SEVIS DATA

Dependent Variable:	Likelihood of Staying Initially			Length of Employment, conditional on staying (in days)			Length of Employment, including all students (in days)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bachelor's	0.039***	0.039***	0.036***	101.2***	98.6***	96.9***	115.3***	109.5***	103.7***
	(0.008)	(0.007)	(0.007)	(6.8)	(6.0)	(5.8)	(10.7)	(9.9)	(9.4)
R-Squares	0.06	0.16	0.19	0.08	0.19	0.20	0.08	0.17	0.21
	(N=233,351 Mean Dep. Var.=0.629)			(N=146,245 Mean=376.8)			(N=233,351 Mean=252.2)		
Master's	0.055***	0.059***	0.062***	162.7***	154.1***	153.2***	185.3***	175.7***	172.0***
	(0.009)	(0.009)	(0.008)	(8.1)	(8.1)	(8.1)	(7.1)	(6.9)	(7.1)
R-Squares	0.13	0.19	0.25	0.12	0.20	0.20	0.17	0.24	0.27
	(N=384,358 Mean=0.757)			(N=290,902 Mean=413.8)			(N=384,358 Mean=319.3)		
Doctorates	0.015**	0.015**	0.021***	90.8***	90.5***	90.6***	107.5***	106.5***	106.6***
	(0.006)	(0.006)	(0.006)	(6.3)	(6.2)	(6.1)	(8.5)	(8.4)	(8.1)
R-Squares	0.11	0.16	0.20	0.07	0.10	0.10	0.11	0.14	0.16
	(N=109,962 Mean=0.769)			(N=84,367 Mean=362.6)			(N=109,962 Mean=323.6)		
Year Fixed-Effects	X	X	X	X	X	X	X	X	X
Field Fixed-Effects	X	X	X	X	X	X	X	X	X
School Fixed-Effects		X	X		X	X		X	X
Demographic Controls			X			X			X

Notes: See notes to Table 1 for the sample restrictions. Each cell is a separate regression. Coefficients are for the binary variable of the OPT policy. Robust standard errors clustered at the field and year level are reported in parenthesis. Sample size (N) and the mean of the dependent variable (for all fields and throughout the sample) by level of study are provided at the bottom of each panel.

***Significant at 1%, ** Significant at 5%, * Significant at the 10%.

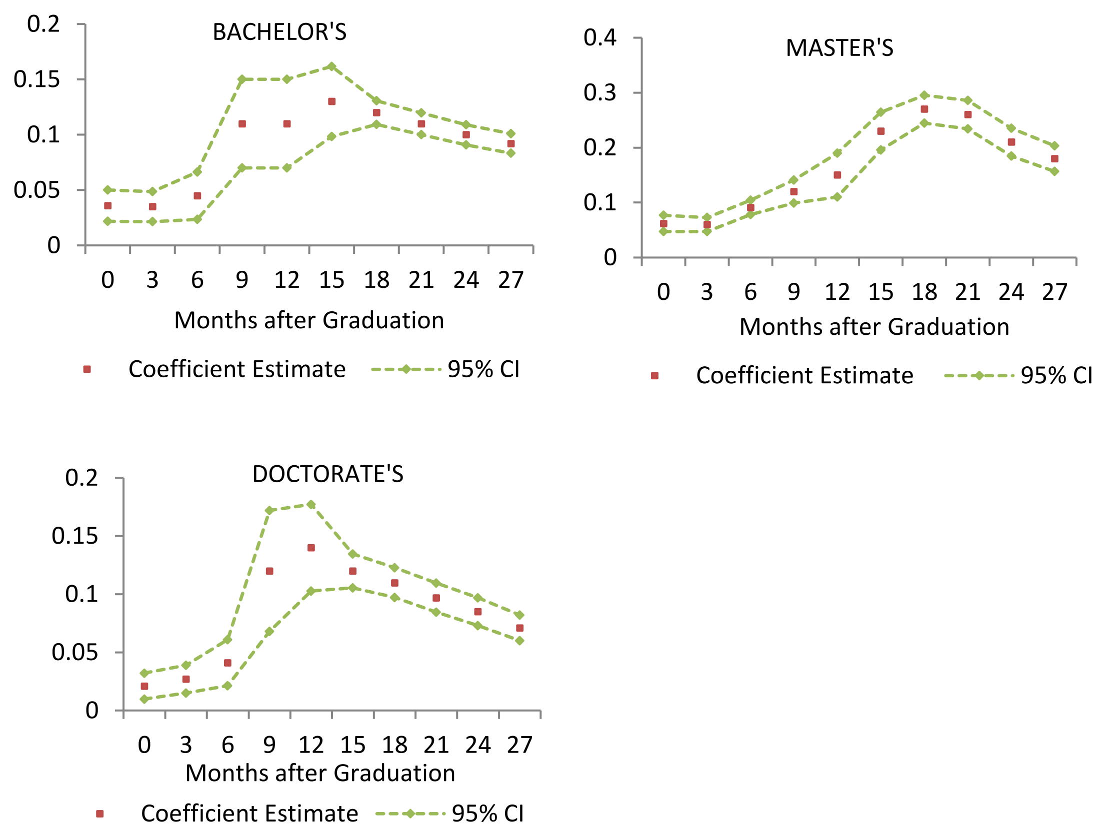
Source: SEVIS data.

The estimates for the likelihood of staying are positive and statistically significant for all specifications at each level of study. The baseline specification has only field and year fixed effects and results in slightly larger point estimates than does the non-parametric difference-in-differences approach (Table 2). Adding school fixed effects and demographic controls has little effect on the point estimates. The regressions with the full set of control variables in Column (3) show that the OPT extension increases the likelihood of staying for students in eligible fields by 3.6 percentage points at the bachelor's level, 6.2 points at the master's level, and 2.1 points at the doctorate level. The estimates for the conditional length of stay follow a similar pattern. The OPT extension increases the employment spell on student visas by 97 days for bachelor's students in eligible fields, 153 days for master's, and 91 days for doctorates.

These results point to the OPT visa policy's role in influencing both the intensive and extensive margin of the postgraduate participation in the U.S. labor market. The coefficients in columns (7)–(9) of Table 3 present the effect of the OPT extension on the employment spell of all students, including those who did not stay. The estimates for this variable are slightly larger than the estimates for the conditional length of stay, with 103 days for bachelor's students, 172 days for master's, and 106 days for doctorates. Because the OPT policy increases the extensive margin of staying, the estimates for the unconditional length of stay capture the increase in this margin along with the intensive measure of length.

Additional specifications consider the likelihood of staying over a range of post-completion intervals from 3 to 27 months (with 3-month increments). Figure 3 displays the impact on these persistence measures from regressions with the full set of control variables. Although the coefficient estimates for the months before 12 are positive, they are considerably smaller than the estimates for the months beyond 12. For instance, students at the master's level become 27 percentage points more likely to stay in the United States beyond 18 months after having completed school (compared with virtually zero levels during the pre-policy period, as staying that long was not possible before the policy). However, students at the same level (masters) become only 6 to 11 percentage points more likely to stay during the months before 12. This asymmetric distribution over the course of OPT is consistent with the two channels of impact discussed in Section II. The estimates for the initial months reflect only the role of the increasing "option value" of U.S. employment due to the improved chances of learning the true match quality, whereas the estimates for the later months capture both this effect and the change in the persistence rates through the continuing employment of those who could not transfer to an H-1B visa until 12 months.

FIGURE 3. THE IMPACT OF OPT EXTENSION ON INTERNATIONAL STUDENTS OVER THE COURSE OF THE OPT PERIOD



Notes: Each point is a coefficient estimate for the binary indicator of the OPT extension and comes from a separate regression in which the dependent variable is the likelihood of staying 3 to 27 months after having graduated (with 3-month increments). All regressions include year, field and school fixed effects and demographic characteristics (age, gender and country of origin fixed effects). The dashed lines represent the 95% confidence interval associated with each estimate.

Source: SEVIS data.

C. Robustness

The validity of the estimates described above depends on the parallel trends assumption between the students' persistence in eligible and non-eligible fields. In the context of the OPT extension, a major concern is the changing labor market conditions due to the Great Recession. To the degree that the Great Recession affected labor demand in eligible fields less adversely, the estimated relative increase in eligible students' persistence might be driven by the recession. However, the observed pattern of the employment lengths mitigates this concern. The average length of employment in eligible fields reached levels beyond 12 months after the extension policy was instituted, while it remained around the legal limit of 12 months in non-eligible fields (Figure 2). Such a divergence can emerge only with the extension policy in work permission. Yet, the recession's role might be a larger concern for the initial stay rates.

Another concern is that the passage of the policy might be endogenous to labor demand conditions in the United States. In particular, the lobbying activity of STEM industries is likely to drive the passage of the OPT extension.[13] For the lobbying activity to be a confounding factor in this analysis, an (expected) increase in the labor demand for foreign STEM workers relative to non-STEM workers must drive both the lobbying and the passage of the OPT extension policy. Some indicators for labor market conditions do not support such a divergence in the labor demand particularly around 2008. For instance, the employment of foreign workers under H-1B visas has been rationed every year since 2004 due to the H-1B cap, and the lobbying activity of STEM industries has been in place since then. Field fixed effects control for the effect of such time-invariant preferences of U.S. firms for hiring foreign STEM workers on the persistence of

[13] The Washington Alliance of Technology Workers sued the U.S. Department of Homeland Security (DHS) over the OPT extension policy, claiming that the policy harmed native workers' employment opportunities, and that the statutorily mandated notice-and-comment period was not followed by the DHS. The Washington Alliance of Technology Workers also referred to the lobbying activity of the Alliance for a Competitive Workforce in the passage of the policy. On November 21, 2014, the U.S. District Court for the District of Columbia invalidated the existing policy on the grounds that the DHS did not follow the proper administrative process in implementing the rule. In response, the DHS proposed a new rule on the OPT extension, considering the proper notice-and-comment period. The new rule, which took effect on May 10, 2016, set the extension period to 24 months and mandated that participants must fulfill the Mentoring and Training Plan form (Form I-983).

international students. Moreover, the Great Recession hit the economy shortly after the policy, making the possibility of positive labor demand conditions in STEM fields after then unlikely. Furthermore, because the cohorts of students that I studied in this paper were already in the United States when the policy was announced, the OPT extension seemed to be a plausibly exogenous factor in their decision to stay.

In this section, I focus on the robustness of the estimates by presenting results from an alternative specification with additional control variables for labor market conditions. First, I use monthly unemployment rates in the state where each student attends college in order to capture the role of local economic activity.[14] Second, I create a field-specific variable to control for changing labor demand conditions at the national level. For instance, if the recession affected the construction sector more adversely and architecture majors are more likely to find jobs in this sector, then their prospects of staying in the United States would be more deteriorated. To capture the effect of such a mechanism on the persistence behavior, I measure the industry-weighted GDP_{ft} for students who complete school in field f in year t as

$$GDP_{ft} = \sum_{n=1}^{N} GDP_{nt} \frac{E_{fn}}{E_f}$$

where the first term, GDP_{nt}, represents the production of the industry n in year t, and the second term represents the time-invariant share of workers in field f who are employed in industry n, which captures the degree to which the employment of students of field f depends on industry n.[15] Third, the recession might also change the demand for foreign and native workers differently. To measure the demand for foreign labor, I employ the U.S. Department of Labor's database for Labor Condition Applications (LCA), which

[14] Ruiz (2014) shows that 45 percent of international students work in the city where their university is located. To the extent that the students' field concentration varies across states, the unemployment rate would control differences in the persistence across fields due to the variation in local labor markets conditions after the Recession. Figure A2 (in the appendix) shows quite a bit variation across states in terms of the share of STEM students, yet there is no correlation between this ratio and the increase in unemployment in the same area.

[15] Field-specific unemployment rates might be more plausible instead of this industry-weighted GDP variable. However, the ACS introduced the field question in 2009 so that the field-specific unemployment variable cannot be constructed for the whole sample period.

provides the field and location of each potential H-1B hire. Because firms do not have to fill the position described in a LCA petition, the total foreign employment calculated from this database is a noisy measure of the actual labor demand. However, as long as this non-compliance behavior does not differ according to the eligibility of fields, this variable serves as a valid control of field-specific foreign labor demand. (See the appendix for details in the construction of these control variables.)

Using these control variables, Figure A2 displays that STEM and non-STEM fields were similarly affected from the recession, and that adverse economic conditions of a state were not correlated with the fraction of international students studying in STEM fields in that state. Table 4 reports the coefficient estimates after adding these variables to the regressions. The coefficients on the local labor market controls are not statistically significant, but the coefficients on the industry-weighted GDP and the field-specific demand for foreign workers are significant. Nonetheless, they have no bearing on the positive relationship between the OPT extension and the persistence.

Furthermore, institutional details of the U.S. visa system provide an additional robustness check to alleviate concerns over differential trends between eligible and non-eligible fields. Citizens of certain countries (Canada, Chile, Mexico, Singapore, and Australia) have access to less restrictive alternative visas. So, they do not rely on H-1B visas for U.S. employment. Therefore, the OPT extension is not supposed to affect the staying prospects of students from these countries.[16] I restrict the analysis to students in eligible fields and use students from these treaty countries as a control group. This alternative DD specification shows that the OPT extension improves the persistence of students from non-treaty countries more, with an exception for the "initial" likelihood of staying at the bachelor's and doctoral levels (Table A3). These results would not be obtained if unobserved labor demand conditions favoring eligible fields were the main factor behind the estimated increase in the persistence from the baseline specification.

[16] The governments of Canada (TN visas), Mexico (TN visas), Singapore (H-1B1 visas), Chile (H-1B1 visas), and Australia (E-3 visas) have special trade treaty agreements with the U.S. government such that their college-educated citizens can temporarily work in the United States without being subject to the H-1B cap.

TABLE 4: IMPACT OF OPT EXTENSION ON INTERNATIONAL STUDENTS AND LABOR MARKET CONDITIONS, ROBUSTNESS

	Bachelor's	Master's	Doctorates
	Likelihood of Staying Initially		
The OPT extension	0.041***	0.067***	0.028***
	(0.007)	(0.007)	(0.007)
Local Unemployment Rate	0.0023	0.0026*	0.0019
	(0.002)	(0.002)	(0.002)
Industry-Weighted GDP	0.51***	0.34***	0.27**
	(0.114)	(0.092)	(0.109)
Field-Specific Labor Demand for Foreign Workers	0.041***	0.026***	-0.0079
	(0.010)	(0.010)	(0.010)
Local Labor Demand for Foreign Workers	-0.014	0.005	0.002
	(0.010)	(0.006)	(0.007)
	Conditional Length of Employment		
The OPT extension	101.4***	149.1***	105.1***
	(6.0)	(8.8)	(6.5)
	Length of Employment		
The OPT extension	137.1***	151.7***	81.3***
	(16.5)	(10.1)	(9.8)
	12-month Stay-rate		
The OPT extension	0.13***	0.16***	0.19***
	(0.021)	(0.022)	(0.022)
	18-month Stay-rate		
The OPT extension	0.12***	0.26***	0.10***
	(0.006)	(0.014)	(0.006)
	24-month Stay-rate		
The OPT extension	0.10***	0.20***	0.082***
	(0.005)	(0.014)	(0.006)

Notes: See notes to Table 1 for the sample restrictions. Each column in each panel is a separate regression. Robust standard errors clustered at field and year level are reported in parenthesis. All regressions control for field and school fixed-effects, as well as demographics (age, age square, gender, and country of origin fixed-effects). Regressions in the first panel additionally control for the state-specific unemployment rate in the month of graduation and the state of the university attended, as well as the field-specific GDP measure in the graduation year. Regressions after the panel additionally control for the annual rate of unemployment and the GDP measure both in the year of graduation and the leading year.

***Significant at the 1 percent level, ** at the 5 percent, * at the 10 percent.

Source: SEVIS data.

Another concern is that students might adjust their graduation timing in response to the recession such that changes in the composition of students might drive the results. Figure A3 illustrates that there were no noticeable compositional changes in terms of completion time after the policy. Nonetheless, I arrange the data by entry classes and restrict the sample to students with similar program completion time. The results are robust to this and some other alternative sample restrictions, such as excluding possible "drop-outs" and using a narrower set of fields as a control group (Table A2).

Finally, students might change their enrollment pattern to STEM programs, and those who enrolled after the OPT extension might have a different tendency to stay in the United States. However, most students in the data were in the United States when the extension policy was announced, and this observation rules out the role of enrollment adjustments. Moreover, I obtain similar estimates after excluding students who started their study after the OPT extension.

D. Heterogeneity in Persistence by Subgroups

By observing the full census of international students, I can explore heterogeneity in the responsiveness to extended OPT terms across subgroups of students defined in terms of country of origin and research intensity of the university attended. For that purpose, I run regressions by interacting the OPT variable with dummy variables associated with each subgroup of interest.

The top panel of Table 5 presents heterogeneity by country of origin for students at the bachelor's and the master's levels, respectively.[17] Indian students are the most responsive subgroup in all measures of persistence, with an average increase in their initial stay rate by 7.2 and 7.4 percentage points and in their conditional length of stay by 119 and 190 days at the bachelor's and the master's levels, respectively. The pattern across the remaining countries is also noteworthy. While the estimates for China and other developing nations are similar to that of India, students from Canada and Europe are less affected.

[17] There is little heterogeneity in treatment effects at the doctoral level, as shown in Table A4.

The bottom panel of Table 5 focuses on heterogeneity by research intensity of the college or university attended.[18] In general, students from universities with lower research intensity (i.e., master's/comprehensive or baccalaureate colleges) are more likely to change their behavior with the policy than are students from top research universities. Estimates at the master's level for students at master's/comprehensive colleges are noticeably high, with the OPT extension inducing a 242-day increase in the length of employment and a 41-percentage point increase in the likelihood of staying 18 months after termination of study.

As discussed in Section II, students aiming to sustain long-term U.S. employment and those on the margin of a successful H-1B application are expected to be more responsive to the OPT extension. The empirical results are consistent with this prediction. Students from non-wealthy nations are more affected because they have stronger incentives to stay in the United States, which provides a substantial wage premium relative to their home country. Master's programs might serve as an appropriate channel for those students because these programs seem to be the least costly investment, whereas bachelor's programs imply expensive tuition bills and doctoral programs imply more forgone earnings. In particular, master's programs at universities with low research intensity might be an easier target with less strict requirements on academic ability and cheaper tuition rates.[19] In addition, students from these low intensity research universities might be constrained by the H-1B cap to a greater extent than the graduates of top research universities, especially if firms give priority to more qualified candidates for costly H-1B positions. Thus, the extended OPT terms increase the employment spells of these constrained students more than others.

[18] The Carnegie classification groups universities based on their research intensity. Research universities in this study combine Research I-II and Doctoral I-II universities. Although all research institutions offer a full range of baccalaureate programs through the doctorate level, they differ by the amount of funds received from the federal government and the total number of doctorate degrees granted. The master's /comprehensive colleges offer a full range of baccalaureate programs through the master's level with at least 20 degrees per year or small doctoral programs, if any.

[19] Average tuition for an out-of-state student is about $32,290 for undergraduate programs at high-intensive research universities while $21,200 for the master's/comprehensive colleges; the tuitions for graduate programs are $29,850 and $15,630, respectively (IPEDS Institutional Characteristics Surveys).

TABLE 5: IMPACT OF OPT EXTENSION ON INTERNATIONAL STUDENTS, HETEROGENEITY BY SUBGROUPS, BACHELOR'S AND MASTER'S LEVEL

Level of Study:	Bachelor's			Master's		
Dependent Variable:	Initial Stay	Length	18-month stay	Initial Stay	Length	18-month stay
By Country of Origin						
China	0.041**	32.3***	0.078***	0.070***	64.3***	0.14***
	(0.019)	(12.3)	(0.010)	(0.010)	(7.0)	(0.008)
India	0.074***	119.5***	0.20***	0.072***	190.2***	0.36***
	(0.016)	(8.1)	(0.012)	(0.009)	(10.2)	(0.018)
Canada	0.0068	44.8***	0.046***	0.02	93.5***	0.070***
	(0.015)	(11.5)	(0.006)	(0.024)	(14.7)	(0.013)
Europe	0.027*	101.9***	0.12***	-0.026*	87.2***	0.11***
	(0.016)	(9.4)	(0.009)	(0.015)	(9.5)	(0.010)
Other	0.033***	99.1***	0.12***	0.041***	92.5***	0.12***
	(0.008)	(5.9)	(0.005)	(0.008)	(7.7)	(0.008)
By University Type						
Research	0.023**	65.0***	0.094***	0.063***	100.3***	0.19***
	(0.009)	(6.9)	(0.006)	(0.008)	(7.0)	(0.008)
Master's/ Comprehensive	0.046***	128.0***	0.14***	0.069***	242.5***	0.41***
	(0.010)	(7.9)	(0.008)	(0.010)	(14.6)	(0.024)
Baccalaureate & Other	0.047***	120.2***	0.14***	0.053***	177.5***	0.31***
	(0.009)	(6.2)	(0.007)	(0.007)	(9.9)	(0.016)

Notes: Each column in each panel is a separate regression. Coefficients are for interaction of the binary variable of the OPT policy and the dummy variable for the subgroup of interest. Robust standard errors clustered at field and year level are reported in parenthesis. Regressions control for year, field, and school fixed effects, as well as demographics (age, age square, gender, and country of origin fixed effects). See notes to Table 1 for the sample restrictions.

***Significant at 1%, ** Significant at 5%, * Significant at the 10%.

Source: SEVIS data.

V. The Consequences on Native Peers in the US Labor Market

Given that the OPT extension increases the supply of international students to STEM fields in the U.S. labor market, how does this change affect labor market opportunities for native recent college graduates? In this section, I describe additional data sources and the empirical analysis employed to answer this question.

A. Data Sources for Labor Market Outcomes of Natives

The American Community Survey (ACS) collects data about the fields of study undertaken at the bachelor's level (but not for advanced degrees) since 2009. I employ the 2009 through 2012 ACS for labor market outcomes of natives in each field and level, using the bachelor's field as a proxy for the field of advanced degrees. I also measure foreign student concentration in each field and level among recent college graduates, combining the ACS and the SEVIS administrative data. However, the ACS does not provide the year when a post-secondary degree is obtained. Instead, I use the following age cut-offs as proxies to calculate the population of recent college graduates in the ACS: ages 24 and younger for bachelor's degree holders, 28 and younger for the master's, and 31 and younger for the doctorates. I choose those age cut-offs based on the modal age of graduation at each level such that the sample will reflect labor market outcomes up to three years after graduation to be consistent with the span of the OPT extension (29 months).[20] I also exclude currently enrolled individuals from the analysis to limit the sample to those who are able to work without any other commitment, yet the results are not sensitive to their exclusion.

[20] The modal graduation age is 22 for natives at the bachelor's, 25 at the master's, and 28 at the doctoral level (2010 National Survey of College Graduates). However, the percentage of those that obtained their master's at age 24 or 26 is very close to those that obtained it at age 25 (the mode). If I use slightly narrower or wider age cut-offs, I obtain similar point estimates, with smaller estimates for the wider age cut-offs (Table 8).

TABLE 6: SUMMARY STATISTICS, LABOR MARKET OUTCOMES OF RECENT GRADUATE NATIVES, ACS AND NSRCG DATA

	Bachelor's		Master's		Doctorates	
Eligibility for OPT extension:	Eligible Fields	Non-Eligible	Eligible Fields	Non-Eligible	Eligible Fields	Non-Eligible
PANEL A: ACS						
Number of Observations	8,501	42,861	3,917	17,930	1,887	2,185
% Female	37.9	62.0	44.0	72.0	50.2	66.3
Mean Age	23.2	23.2	26.3	26.4	29.0	28.6
% White	79.0	80.6	79.8	82.8	85.2	83.6
% Asian	7.2	3.9	8.1	3.1	6.1	5.5
% Black	6.6	7.7	6.7	7.9	4.2	5.4
% Hispanics	3.1	3.8	2.2	2.7	1.9	1.8
% Employed	87.6	88.0	93.1	92.9	94.5	93.6
% Full Year Full Time Employed	59.4	58.2	79.0	76.3	82.4	80.6
Mean Annual Earnings	29,912	24,074	52,566	40,382	66,021	65,650
% Foreign Students						
in 2009	0.91	0.67	7.19	2.90	9.07	3.11
in 2010	0.80	0.62	7.96	2.89	7.89	3.05
in 2011	0.84	0.64	10.47	3.03	8.70	2.94
in 2012	0.88	0.67	10.25	2.98	9.56	3.31
PANEL B: NSRCG						
Number of Observations	5,224	3,357	3,425	2,585	.	.
% Employed	90.0	90.8	95.5	93.7	.	.
% Reason for part-time or unemployment: no jobs	53.8	50.4	48.2	33.8	.	.
% Job Related to Field	74.9	63.3	85.5	78.6	.	.

Notes: Both panels include recent graduate natives who are not currently enrolled in school. To define the sample of recent graduates in ACS, I use ages 24 and younger for bachelor's degree holders, 28 and younger for the master's, and 31 and younger for the doctorates. Average annual earnings are reported in 2009 prices, conditional on employment. % Foreign Students is calculated as the percentage share of F-visa students (from SEVIS data) among the population of all recent college graduates in the same field and time (from ACS). "Eligible" fields refers to STEM fields eligible for the OPT extension.

Source: 2009-2012 ACS in Panel A, and 2008 and 2010 NSRCG in Panel B.

Panel A of Table 6 presents the summary statistics that disaggregate students by highest completed degree and by whether the field of their bachelor's degree is eligible for the OPT extension. After excluding those enrolled at school for another post-secondary degree, the percentage of recent graduates who are currently employed is around 90 percent overall in both eligible and non-eligible fields, and it slightly increases with the level of study. The percentage of those employed full-year and full-time during the preceding year (i.e., worked at least 40 weeks and usually work 35 hours per week) is similar between eligible and non-eligible fields at each level. Yet, it is significantly lower among the bachelor's (at around 60 percent) than among the advanced degree holders (at around 80 percent). Finally, annual earnings increase with the attainment of advanced degrees as expected, with an especially high premium for master's degrees in STEM fields.

I supplement the analysis with the National Survey of Recent College Graduates (NSRCG) because of possible measurement errors induced by not observing the date of graduation and the field of advanced degrees in the ACS. The NSRCG, administered by the National Science Foundation every two years, provides labor market outcomes of recent college graduates in the fields of science, engineering, and health at the bachelor's and master's levels along with relevant educational characteristics. The percentage of currently employed is around 90 percent in the NSRCG data, consistent with the ACS. The NSRCG data also notably show that 48.2 percent of the unemployed graduates with a STEM master's degree claim the unavailability of jobs as the reason for unemployment, whereas only 33.8 percent of the unemployed claim this reason in non-STEM fields (Panel B of Table 6).

B. Research Design: IV Analysis

I am interested in how the supply of foreign students to the U.S. labor market affects the employment of native workers and their earnings. To quantify this effect, I estimate

$$(2) \qquad Y_{i_{ft}} = \beta_0 + \beta_1(\%\,Foreign\,Students)_{ft} + \beta_2 X_{i_{ft}} + \delta_t + \delta_f + \epsilon_{i_{ft}}$$

where $Y_{i_{ft}}$ is the outcome variable of interest in time t for native individual i who is a recent graduate with a degree in field f. The variable $(\%\,Foreign\,Students)_{ft}$ represents the percentage share of international students on OPT from field f in time t among the population of all recent college graduates in the same field and time. I employ the SEVIS data used earlier to calculate the relevant international student population for the numerator and the ACS (or the NSRCG depending on where the dependent variable comes from) to calculate the population of all recent graduates for the denominator.[21] I also control for several demographic variables (gender, age, age squared, and race/ethnicity) and state-specific unemployment rates to capture local labor demand conditions. In addition, I include year and field fixed effects (δ_t and δ_f, respectively) to capture the impact of national macroeconomic conditions and permanent differences in earnings and employment across majors.

An important concern about this model is whether $(\%\, Foreign\, Students)_{ft}$ is exogenous to the other unobserved factors ($\epsilon_{i_{ft}}$) influencing the native employment and earnings. For instance, natives might earn higher wages in a particular field due to positive productivity shocks experienced in that field, whereas the same productivity conditions might also attract more foreign students from that field to the U.S. labor market. In such circumstances, the OLS estimates of equation (2) would understate the negative relationship between native earnings and foreign employment. Alternatively, the OLS estimates might overstate the negative relationship between native employment and high prevalence of foreign students. For instance, if natives are less interested in working in particular fields because of undesirable working conditions, such as long hours, then U.S. firms might meet their demand for labor with international graduates in these fields. In that case, the negative relationship between native and foreign employment would be due to reverse causality.

C. The OPT Extension as an Instrument

The OPT extension, which increases the persistence of foreign students in STEM fields as shown in Section IV, serves as a plausible exogenous change in the supply of foreign students, because it is likely to be independent of unobserved factors related to natives' labor market outcomes. To isolate the shift in labor supply resulting from the OPT extension, I measure the extra labor supply by foreign students, the variable

[21] Foreign students' labor supply is calculated as the weighted sum of employment during the reference year; where the fraction of 365 days a foreign student worked on OPT serves as the weight. The reference period is defined as the preceding 12 months from the reference month in the ACS and NSRCG. Although the ACS is conducted in all months over the year, the publicly available files do not release the month of the interview. Thus, I assume July (the middle of the year) as the reference month in the ACS, while it is known to be October in the NSRCG.

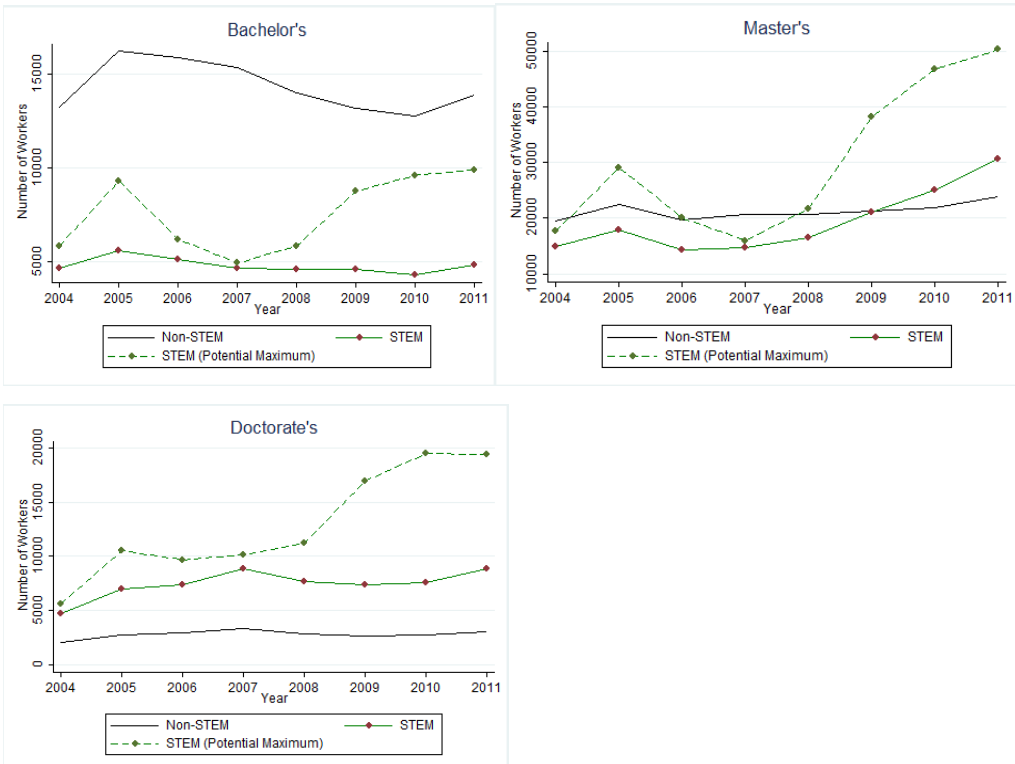
$(Number\ of\ OPT\ Extension\ Eligibles)_{ft}$, under the counterfactual scenario that all students would have stayed in the United States after graduation and continued to work under the OPT extension. I then use this variable as the instrumental variable for $(\%\ Foreign\ Students)_{ft}$. The key identifying assumption is that parameters of the policy (i.e., eligibility of fields and length of extension) are not related to unobserved determinants of labor market outcomes, such as productivity shocks.[22]

Figure 4 illustrates the labor supply shock tied to the OPT extension. The figure presents the total labor supply by foreign students in STEM and non-STEM fields each year since 2004. Whereas the pattern of the supply at the bachelor's and the doctoral levels does not visibly differentiate between STEM and non-STEM fields after the policy was implemented, the increase in the supply of STEM master's students is noteworthy. To understand the role of the OPT extension in this increase, I look at the maximum potential labor supply while assuming that all students would have stayed and continued to work until the end of their OPT terms. This supply measure increases in STEM fields after the policy's implementation as expected, and its correlation with the actual labor supply is apparent at the master's level.[23]

[22] Although I cannot completely rule out the possibility that the OPT extension policy was introduced because of lobbying activities of the tech industry to meet their increased demand for STEM workers, the policy lags alleviate concerns on this issue. The OPT extension was introduced in 2008 after two consecutive years when the H-1B cap was fulfilled in the first week of applications. However, the Great Recession hit the U.S. economy right after the OPT extension policy and the H-1B cap was not met in the first week of applications again until 2013.

[23] A concern is that firms use the OPT term to substitute employment via costly H-1B visas so that the total supply of foreign students to the U.S. labor market would not increase at all after the OPT extension. However, the aggregate statistics of H-1B visas rule out this possibility. Even though the number of international students transferring to the H-1B visa is not available, the percentage of initial H-1B visas issued to the aliens residing in the United States (presumably international students) are pretty much steady over the sample period.

FIGURE 4. THE LABOR SUPPLY BY FOREIGN STUDENTS ON STUDENT VISAS



Notes: The solid lines display the total supply by F-visa students in each field, while the one with marker points represents eligible STEM fields and the other one shows non-STEM fields. The dashed line with marker points displays the potential maximum labor supply by F-visa students, calculated while assuming that all students would have stayed in the U.S. labor market and continued to work until the end of OPT terms (i.e., always 12 months in non-eligible fields, 12 months in eligible fields before the OPT extension and 29 months afterward).

Source: SEVIS data.

It is also important to point out that the labor supply in STEM fields does not display a jump in 2008 because of the nature of the extension policy. When the extension was announced in 2008, only graduates of the 2007 class who were already in the United States on student visas were eligible for the 17-month extension because only these students were completing the initial 12 months of their OPT. As a result, we observe only a slight increase in the labor supply from 2007 to 2008. However, in 2009, both graduates of the 2008 class who were completing their 12 months of OPT and graduates of the 2007 class who were completing their 24 months were eligible to work under OPT. For that reason, the increase in the labor supply from 2008 to 2009 was even higher than was the increase in the previous year. Thus, the new policy created a gradual increase in the labor supply until all relevant cohorts reached the limits of work permission.[24] This unique growth pattern in the labor supply to STEM fields seemed unlikely to have been driven by unobserved labor demand in those fields during the Great Recession, mitigating concerns over the OPT extension policy's endogeneity.

The bottom panel of Table 7 presents the first-stage regression results. The estimates show a positive and statistically significant relationship between the instrument and the foreign student shares at the master's level. A one unit increase in the instrument (where the mean is 2.39, representing 2,390 students) explains a 1.27 percentage point increase in the share of foreign students. However, the regressions at the bachelor's and doctoral level do not provide any statistically significant relationship.

D. Regressions Results from ACS

Table 7 reports both the OLS and the IV results for the following native outcomes of interest: (1) whether the individual is currently working at the time the survey is conducted, (2) whether the individual worked at least 40 weeks and 35 hours per week (full-year full-time or FYFT) in the preceding 12 months, (3) the logarithm of annual income earnings in the preceding 12 months for those who worked at least one week, and (4) the logarithm of annual income earnings for FYFT workers. Each cell represents the coefficient estimates (with robust standard errors clustered at the field and year level) for the variable $(\%\,Foreign\,Students)_{ft}$, where the level of degree and field of study determine the relevant foreign student share for each observation.

While the estimates at the bachelor's and the doctorate levels are not statistically significant and have weak first stages, the IV estimates at the master's level suggest important results. A 1-point increase in the foreign student share in a particular field decreases the likelihood of current employment by 0.3 percentage points and FYFT

[24] The growth trend in the enrollment of STEM students before the policy might create a measurement error in the instrument. To address this concern, I measure the growth trajectory of each field under the counterfactual scenario that all students would have initially stayed and continued to work only 12 months (regular OPT). Results from the regressions with the instrument adjusted for this growth trajectory are very similar to the baseline estimates (Table 8).

employment by 0.7 percentage points for natives in the same field. As the representation of foreign students in STEM fields increases by about 3 percentage points at the master's level over the sample period, these IV estimates indicate a 0.9 percentage point decline in current employment and a 2.1 percentage point decline in FYFT employment overall. As students who major in STEM fields have an average employment rate of about 93 percent and average FYFT employment of about 79 percent, the estimates show a roughly 13 percent increase in unemployment (i.e., 0.9 percentage points out of 7) and a 10 percent increase in the FYFT unemployment (i.e., 2.1 percentage points out of 21).

In addition to the adverse effects on employment, the IV estimates show a downward pressure on earnings. A one percentage point increase in the share of foreign students decreases earnings of employed natives who studied in the same field by about 1.6 percent. This estimate indicates that a 10 percent increase in the labor supply of foreign students is associated with a 1.4 percent decrease in native earnings (calculated at the mean value of foreign student share in STEM fields).

One would also like to know whether the decline in annual earnings is due to a decrease in unit skill prices or a decrease in total hours worked associated with crowding out. Unfortunately, the ACS reports the numbers of weeks worked as a categorical variable, which makes the calculation of hourly wages unfeasible without further assumptions. Instead, I estimate the impact on earnings of full-time full-year native workers and find no statistically significant effect. Thus, the decline in earnings is primarily driven by the decrease in total hours worked.

TABLE 7: IMPACT OF FOREIGN STUDENTS ON LABOR MARKET OUTCOMES OF RECENT GRADUATE NATIVES, BASELINE FIRST STAGE AND IV REGRESSION RESULTS, ACS

Dependent Variable:	Currently Employed		Full-Year Full-Time Worked		Log Annual Earnings		FTFY Log Earnings	
Regression Method:	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Master's Sample (N=21,847)	-0.0005	-0.0032**	-0.0053**	-0.0072***	-0.0031	-0.0166***	0.0054	0.0011
	(0.0013)	(0.0016)	(0.0020)	(0.0028)	(0.0060)	(0.0040)	(0.0043)	(0.0045)
	(Mean Dep. Var.=0.929)		(Mean=0.768)		(Mean=10.43)		(Mean=10.67)	

	First Stage Results
Bachelor's	The first stage coefficient=-0.13, t-statistics=-0.91, and F-statistics=0.83
Master's	The first stage coefficient=1.27, t-statistics=7.45, and F-statistics=55.48
Doctorates	The first stage coefficient=0.38, t-statistics=0.68, and F-statistics=0.46

Notes: Each cell is a separate regression. Coefficients are for the percentage of F-visa students in each field. See Table 7 for its definition and sample restrictions. Robust standard errors clustered at field and year level are reported in parenthesis. Regressions control for year and field fixed effects, state-level unemployment, and demographics (age, age square, gender, and race/ethnicity). Estimates are weighted with person weights provided by the ACS. The instrument is the number of workers that would be eligible for the 17-month OPT extension (mean=0.46 at the Bachelor's; mean=2.39 at the Master's; and mean=0.98 at the Doctorates level with unit=1000). The sample sizes are smaller for the annual earnings because those not worked last year are dropped from the sample. ***Significant at 1%, ** Significant at 5%, * Significant at the 10%.

E. Robustness

The instrument mitigates concerns about unobserved factors which might influence both foreign student share and native student outcomes, yet one might still worry that the Great Recession affected eligible fields more adversely than it affected non-eligible fields.[25] The following three pieces of evidence alleviate these concerns. First, the regressions with the controls for labor market conditions (as described in Section IV) provide similar and even slightly more negative estimates (Table 8). Second, I find no statistically significant impact on labor market outcomes of more experienced native workers (i.e., those between 35 and 50). If field-specific conditions were driving the results, we would likely observe some negative effects on the experienced STEM

[25] A related concern is that the Great Recession might change graduation timing. This might undermine the validity of the instrument, which depends on international students' graduation timing and it might also generate compositional changes among recent graduate natives seeking jobs in the labor market. However, the SEVIS data show that international students do not delay their graduation, especially at the master's level (Figure A3) and the composition of native students, in terms of gender, race, and fields of study, is stable during the recession (Figure A4).

workers. Third, when I run the regressions separately for states that were less affected from the recession and for the ones more affected, I find similar negative estimates in both cases (Table A5). If the recession was driving the results, we would observe no or smaller effects on native workers in the less affected states.

TABLE 8: IMPACT OF FOREIGN STUDENTS ON LABOR MARKET OUTCOMES OF RECENT GRADUATE NATIVES, ROBUSTNESS CHECKS, IV ESTIMATES AT THE MASTER'S LEVEL

Dependent Variable:	Currently Employed	Full Year Full Time Employed	Log Earnings
Baseline Results from Table 7	-0.0032**	-0.0072***	-0.0166***
	(0.0016)	(0.0028)	(0.0040)
Including those who enrolled in school	-0.0028*	-0.0065***	-0.0168***
	(0.0015)	(0.0016)	(0.0031)
Controlling for industry-weighted GDP	-0.0040**	-0.0075**	-0.0181***
	(0.0019)	(0.0032)	(0.0049)
Using narrower age cut-offs to define recent graduates	-0.0048**	-0.0056	-0.0143***
	(0.0022)	(0.0043)	(0.0046)
Using wider age cut-offs to define recent graduates	-0.0023	-0.0036	-0.0034
	(0.0015)	(0.0023)	(0.0029)
Adjusting the instrumental variable for the pre-existing growth trend in enrollment	-0.0033	-0.0060*	-0.0172***
	(0.0024)	(0.0036)	(0.0048)
Impact on the experienced natives (between ages 35 and 50)	0.0008	-0.0013	-0.002
	(0.0010)	(0.0011)	(0.0019)

Notes: Each cell is a separate regression. Coefficients are for the percentage share of F-visa students in each field and level. See notes to Table 7 for the instrumental variable's definition, the list of other variables employed in regressions. Narrower age-cutoffs refer to the sample of one-age younger individuals at each level, while wider age-cutoffs refer to the one-age older sample. The sixth row adjusts the instrumental variable for the pre-existing growth trajectory, which is calculated under the counterfactual scenario that all students would have initially stayed and continued to work only 12 months (see footnote 21).

***Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Source: 2009-2012 ACS.

To address concerns over the measurement error introduced by the assignment of fields for advanced-level degrees and the approximation of graduation age in the ACS analysis, I run a similar analysis with the NSRCG, which is not subject to this source of measurement error. The results show a crowding out in employment with slightly larger estimates than those of the ACS analysis (Table 9). In addition, the NSRCG provides more insights about the relevant labor market activities by reporting the reason for unemployment or part-time work and the relevance of jobs to the field of study.[26] I find a positive relationship between the presence of foreign students in a particular field and the likelihood of reporting "no jobs available" as the reason for un- or underemployed natives in the same field. While that finding supports the hypothesis that foreign students tighten employment opportunities for native counterparts, it does not seem that natives are pushed to accept jobs unrelated to their field, as the estimated effect of international student supply on the relevance of one's job to the original field is not statistically significant.

TABLE 9: IMPACT OF FOREIGN STUDENTS ON LABOR MARKET OUTCOMES OF RECENT GRADUATE NATIVES, BASELINE REGRESSION RESULTS, NSRCG

	Employed		Reason for unemployed: no job available		Related to Field of Study		Employed (ACS with NSRCG fields)	
Dependent Variable:	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Master's Sample (N=6,010)	-0.0046** (0.0019)	-0.0051** (0.0023)	0.066*** (0.0220)	0.077*** (0.0190)	-0.0013 (0.0028)	-0.00086 (0.0028)	-0.0019 (0.0012)	-0.0030* (0.0016)
	(Mean Dep. Var.= 0.947)		(Mean=0.363)		(Mean=0.798)		(Mean= 0.931)	

	First Stage Results
Bachelor's Sample	The first stage coefficient=9.95E-7, t-statistics=0.01, and F-statistics=0.016
Master's Sample	The first stage coefficient=0.79, t-statistics=5.72, and F-statistics=33.98

Source: Each cell is a separate regression. Coefficients are for the percentage of F-visa students in each field. See Table 8 for its definition and sample restrictions. Robust standard errors clustered at field and year level are reported in parenthesis. Regressions control for year and field fixed effects, and demographics (age, age square, gender, and race/ethnicity). Estimates are weighted with person weights provided by NSF. The instrument is the number of workers that would be eligible for the 17-month OPT extension (mean=0.46 at the Bachelor's; mean=2.31 at the Master's with unit=1000). The sample sizes are 1,767 at the Bachelor's and 886 at the Master's level for estimates of the reason in the third and fourth columns. ***Significant at 1%, ** Significant at 5%, * Significant at the 10%.

[26] The NSRCG asks questions about the annual salary, the number of weeks worked, and usual hours. However, these instruments are collected only from those who are currently employed. This survey process might introduce serious selection issues, as those currently unemployed might have very different characteristics in those aspects. Thus, I do not use these variables to compare with the ACS results.

F. Comparing Potential Costs and Benefits

The estimated negative effects on native STEM workers at the master's level must be balanced against the possible productivity gains arising from retaining international students in the United States (Chellaraj et al. 2008, Hunt and Gauthier-Loiselle 2010, Kerr and Lincoln 2010, Stephan 2010, Stuen et al. 2012, Moser et al. 2014). To compare potential costs and benefits, I calculate the necessary gains in earnings for native workers of the same age range in industries where foreign STEM graduates work predominantly, such that these benefits would offset the earnings loss that I estimate for natives who are recent STEM master's graduates as[27]

$$\underbrace{-4.8}_{\substack{estimated\ decline\ in\ earnings \\ of\ recent\ graduate \\ \text{native } STEM\ master's}}\% \quad x \quad \underbrace{\$52{,}566}_{\substack{average\ earnings \text{ of} \\ \text{recent graduate} \\ \text{native } STEM\ master's}} \quad x \quad \underbrace{0.042}_{\substack{share\ of\ native\ STEM\ master's \\ among\ all\ native\ workers\ (ages\ 22\ and\ 28) \\ in\ relevant\ STEM\ industries}}$$

$$= \quad \boxed{\underbrace{\mathbf{0.36\%}}_{\substack{balancing\ increase\ in \\ earnings\ of\ other\ natives\ in \\ the\ same\ age\ and\ STEM\ industries}}} \quad x \quad \underbrace{\$30{,}351}_{\substack{average\ earnings \\ of\ other\ natives}} \quad x \quad \underbrace{0.958}_{\substack{share\ of\ other \\ natives}} \; .$$

This analysis shows that a 0.36 percent increase in earnings of other natives of the same age and industries is necessary to offset the estimated 4.8 percent loss in earnings of recent STEM master's.

Furthermore, I calculate the necessary elasticity of patenting with respect to the international student share by decomposing the 0.36 percent increase in earnings as

$$0.36 = \boxed{\underbrace{\mathbf{13.8}}_{\substack{balancing\ elasticity \\ of\ patenting\ w.r.t. \\ international\ student\ share}}} \quad x \quad \underbrace{0.24}_{\substack{increase\ in\ international \\ \text{student share } observed\ in \\ SEVIS\ data\ after\ OPT\ extension \\ (combining\ all\ levels\ \ of\ study)}} \quad x \quad \underbrace{0.11}_{\substack{elasticity\ of\ GDP \\ w.r.t.\ patenting \\ (Furman\ et\ al. 2002)}}$$

[27] Because most engineering and computer science majors work in manufacturing, finance and insurance, and professional and technical services industries, I concentrate on native workers in these industries as a plausible group to experience potential spillover effects instead of all natives. Also, as we saw in Part C of Section V, the decline in annual earnings is primarily driven by a decrease in total hours worked. Thus, using only the negative effects on native's annual earnings in this analysis should be a sufficient statistic to capture all the negative effects, including the one on employment.

where the multiplication of the first two terms represents the contribution of international students to the U.S. patenting stock, and the last term converts this contribution to an increase in average earnings. This analysis shows that the necessary 0.36 increase in earnings can be achieved if the elasticity of patenting with respect to the international student share is 13.8. This figure is consistent with estimates in the literature, such as Hunt and Gauthier-Loiselle (2010) finding the patenting elasticity in the order of 9 to 18 with respect to the share of college graduate foreign workers.

In sum, although the earnings loss estimated earlier for STEM master's students is relatively large, master's students comprise a small fraction of the labor force. So, all other workers would need only a small increase in earnings to offset the negative effects in the aggregate. The observed increase in the international student share after the OPT extension seems enough to achieve the increase in earnings for natives in the same age range and industries based on estimated patenting elasticities in the literature, and their contributions could be even larger if workers in other industries and older workers benefit as well.

VI. Conclusion

This analysis demonstrates that a 17-month extension of the OPT visa increases international STEM students' access to the U.S. labor market, especially at the master's level. Moreover, the increase in their labor supply reduces employment and earnings of natives who study in STEM fields. Some U.S. policy makers recently proposed allocating more permanent visas for international STEM graduates in order to boost U.S. productivity, whereas Canada, as another major destination country for highly-skilled immigrants, already gives priority in permanent visa applications to international STEM graduates of Canadian and foreign universities, even if they do not have a Canadian job offer. My results suggest that the current proposals would increase the supply of international students in the U.S. labor market.

The estimated negative impact of the OPT extension on natives' labor market outcomes raises concerns, especially given prior research on the effect of early career setbacks on negative outcomes in the long run (Oreopoulos et al. 2006). However, highly-skilled immigrants contribute to patenting and publishing activities, and some studies show that immigrants have positive spillover effects on earnings of college-educated natives. This spillover effect might occur through total factor productivity growth or natives' shift towards complementary occupations requiring greater communication skills, such as high-paying managerial jobs (Peri and Sparber 2011, Hunt 2011, Peri et al. 2014). My comparison of potential costs and benefits in the previous section shows that the losses of native STEM master's due to the OPT extension could be offset by the gains in average earnings of other natives through an overall productivity increase.

Finally, while this paper offers a starting point in analyzing effects of the OPT extension, it focuses on the short-term outcomes among students already in the U.S. at the time of the policy change. Students might adjust in other margins as well, such as changing their university enrollment patterns or their transitions to H-1B visas and permanent residency in the long run. These adjustments might have further effects on native peers who are potentially interested in STEM fields. A longer window of analysis is needed to understand how the behavioral changes induced by the OPT extension affect long-term persistence, innovation, and labor market outcomes of foreign-born graduates of U.S. universities.

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APPENDIX

(The appendix includes extra explanation which is related to Chapter 2)

A1. Codes for Field of Study

The field of study in SEVIS data is reported with the Classification of Instructional Programs (CIP) codes. This coding scheme was developed by the National Center for Education Statistics to maintain education statistics consistently for all federal agencies. As the designation of eligibility for the OPT extension is also reported with the CIP codes, I identify eligible fields in the persistence analysis without using any approximation.

While the two-digit CIP series (with 48 groups) represent the most general groupings of related programs and the four-digit CIP series (with 420 groups) at the intermediate level, the six-digit CIP series (with about 1,730 groups) represent specific instructional programs. Although the designation for the eligibility was made with the six-digit CIP codes and they seem ideal to capture field-specific effects, there were only a few or even no foreign students in some fields. Thus, I collapse the six-digit CIP series into 185 fields. In doing so, I ensure that every field within the same aggregated category has the same eligibility status and follows a similar growth trend and that the aggregate category contains a sizable number of observations. The crosswalk from the six-digit CIP series into my aggregation, along with the OPT eligibility status of each field, is available on the author's website.

Unlike the SEVIS data, the ACS reports the field of study with its own classification. Although these codes are different from the CIP codes, I easily merge them with the aggregated CIP codes due to the detailed level of reporting in the ACS, with about 200 codes. However, I further collapse the merged fields into 44 categories because the sample sizes otherwise were fairly small and subject to measurement error, as I only use the recent college graduates in this study. The crosswalk between the ACS codes (as reported in the IPUMS extracts) and my aggregation is provided on the author's website. Finally, the NSRCG reports fields with its own coding scheme and a crosswalk is provided online by NSF to match the CIP codes.

A2. Construction of Variables for Labor Market Conditions

I use unemployment rates from the Bureau of Labor Statistics (BLS) as a measure of local economic activity. To construct the industry-weighted GDP variable, I employ the annual industrial production records from the Bureau of Economic Analysis (BEA). The data are provided with the following 19 industry groups: agriculture, forestry, fishing, and hunting; mining; utilities; construction; manufacturing; wholesale trade; retail trade; transportation and warehousing; information; finance and insurance; real estate and rental and leasing; professional and technical services; management of companies and enterprises; administrative and waste services; educational services; health care and social assistance; arts, entertainment, and recreation; accommodation and food services; and other services except government.

I create a field-specific GDP measure as the weighed sum of industrial production where the weights are the employment dependency of each major on industries. To address concerns over an endogenous change in the industrial composition, I employ individuals ages 35–50, a group whose labor market performance is not affected by the OPT extension (Table 8). I demean and detrend this variable and use it in the regressions as a measure of the percentage deviation from the long-run average of each field.

To measure the labor demand for foreign workers, I employ the U.S. Department of Labor LCA database, which provides the occupation and location of each foreign hiring under the H-1B status. I create a national and local level control variable for foreign labor demand out of this data set. First, I aggregate applications by state and year as a measure of local foreign demand. Second, I aggregate them by occupation at the national level. I use the following 10 aggregate occupations: architects, teachers and professors, computer scientists, engineers, physical scientists, biological scientists, social scientists, health occupations, managerial occupations, and all other occupations. I use the values of these variables net of field fixed or state fixed effects as a measure of the percentage deviation from the long-run average.

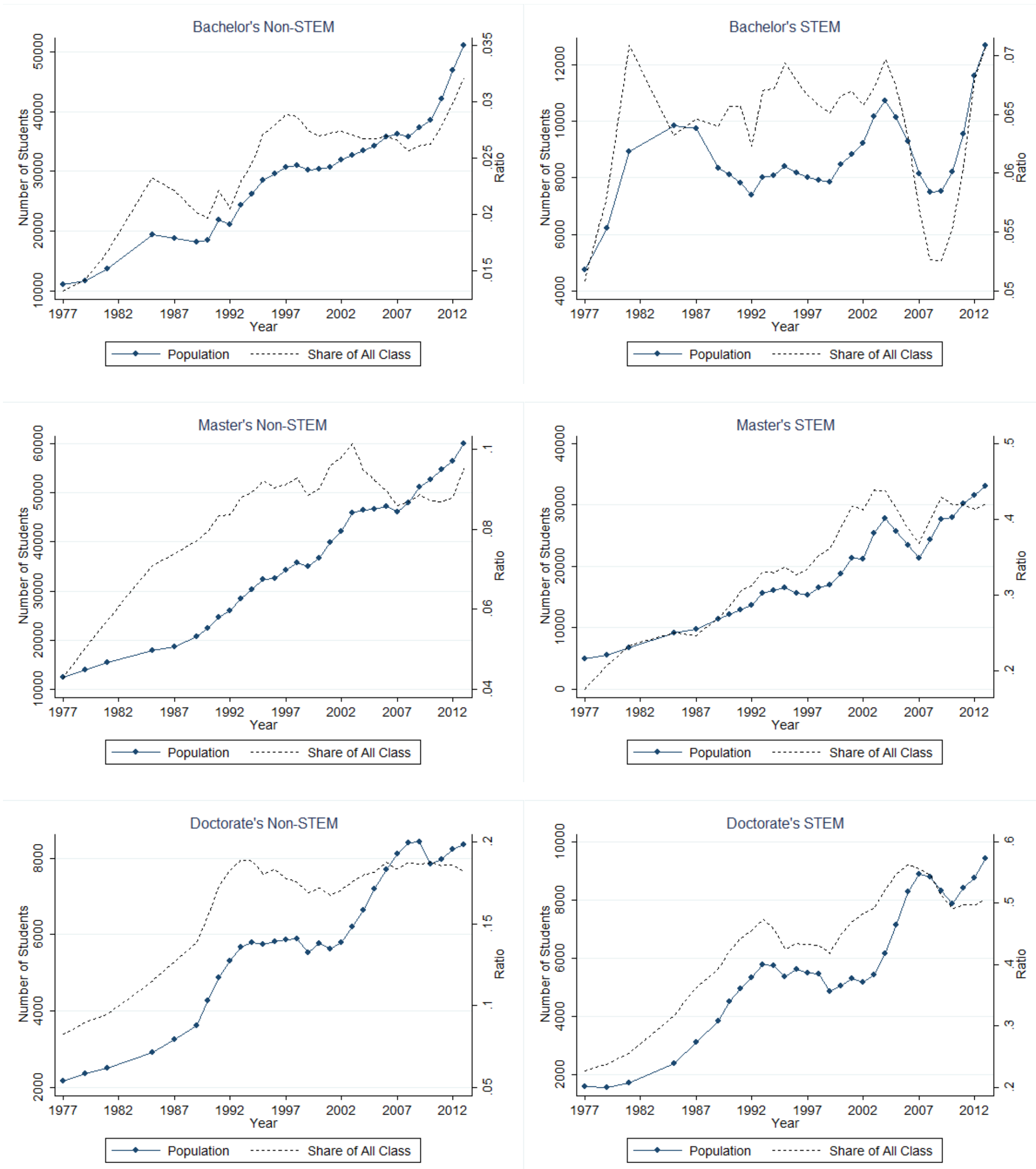
Figure A2 of the appendix demonstrates the variation in these labor market controls by differentiating STEM and non-STEM fields. In all measures, it is evident that the employment opportunities were adversely affected after the OPT extension due to the Great Recession. The industry weighted-GDP measure displays very similar trends between the two fields. The hiring of foreign STEM workers recovered more rapidly than the non-STEM occupations although most of this rapid recovery is driven by the computer occupations. Finally, there is no noticeable correlation between the rise in the unemployment rate in a state and the fraction of international students in STEM fields in that state.

A3. Robustness on Persistence of International Students

Table A2 presents the robustness of results to a number of alternative sample restrictions. The second row provides estimates by including those who adjusted their visa status before the school completion date. The third row addresses concern over endogenous time to degree and right censoring due to the sample restrictions by graduation classes. I arrange the data by entry class and restrict the sample by the duration of program completion. More specifically, I restrict the bachelor’s sample to students from the 2000 to 2007 entry class who completed study in six years, the master’s sample to those from the 2002 to 2010 class who completed study in three years, and the doctorate sample to those from the 1999 to 2006 class who completed study in six years. The fourth row drops those who finished a bachelor’s or doctoral program in less than two years and a master’s program in less than 180 days from the sample because those might be the possible dropouts from the school who did not earn a degree. The fifth row excludes those who started school after the policy announcement, allowing a one year application delay to address concerns about the compositional changes of new students, as those students might have different unobserved persistence. Namely, I exclude those who started in the 2010 Academic Year and later. Finally, the sixth row addresses the concern over the control group's selection. I restrict the sample to science, engineering, and health-related fields in line with the NSF's sampling frame for science and engineering statistics as discussed in Section IV.

A4. Figures

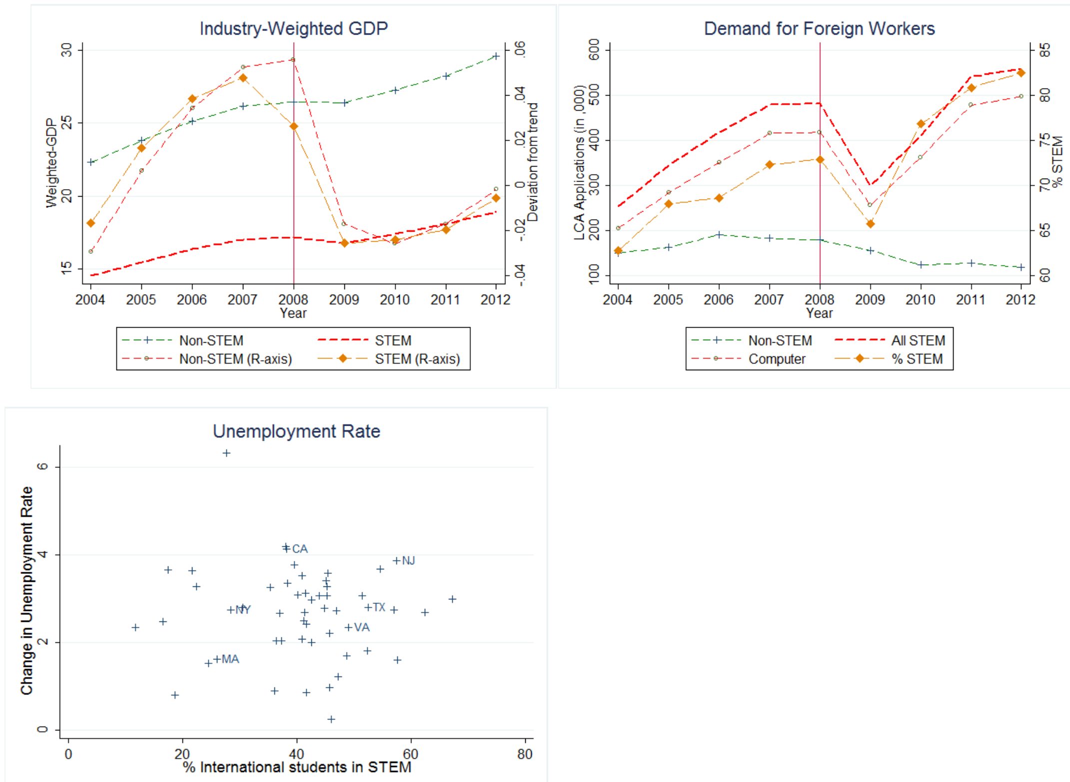
FIGURE A1: TRENDS IN DEGREES CONFERRED TO INTERNATIONAL STUDENTS, BY FIELD AND LEVEL



Notes: STEM fields include computer sciences, engineering, physical and biological sciences, agricultural and environmental sciences. Solid lines represent total number of degrees granted to students with temporary visas. Dashed lines represent the ratio of degrees granted to students with temporary visas among all the degrees granted.

Source: IPEDS 1977-2013, Completion Surveys.

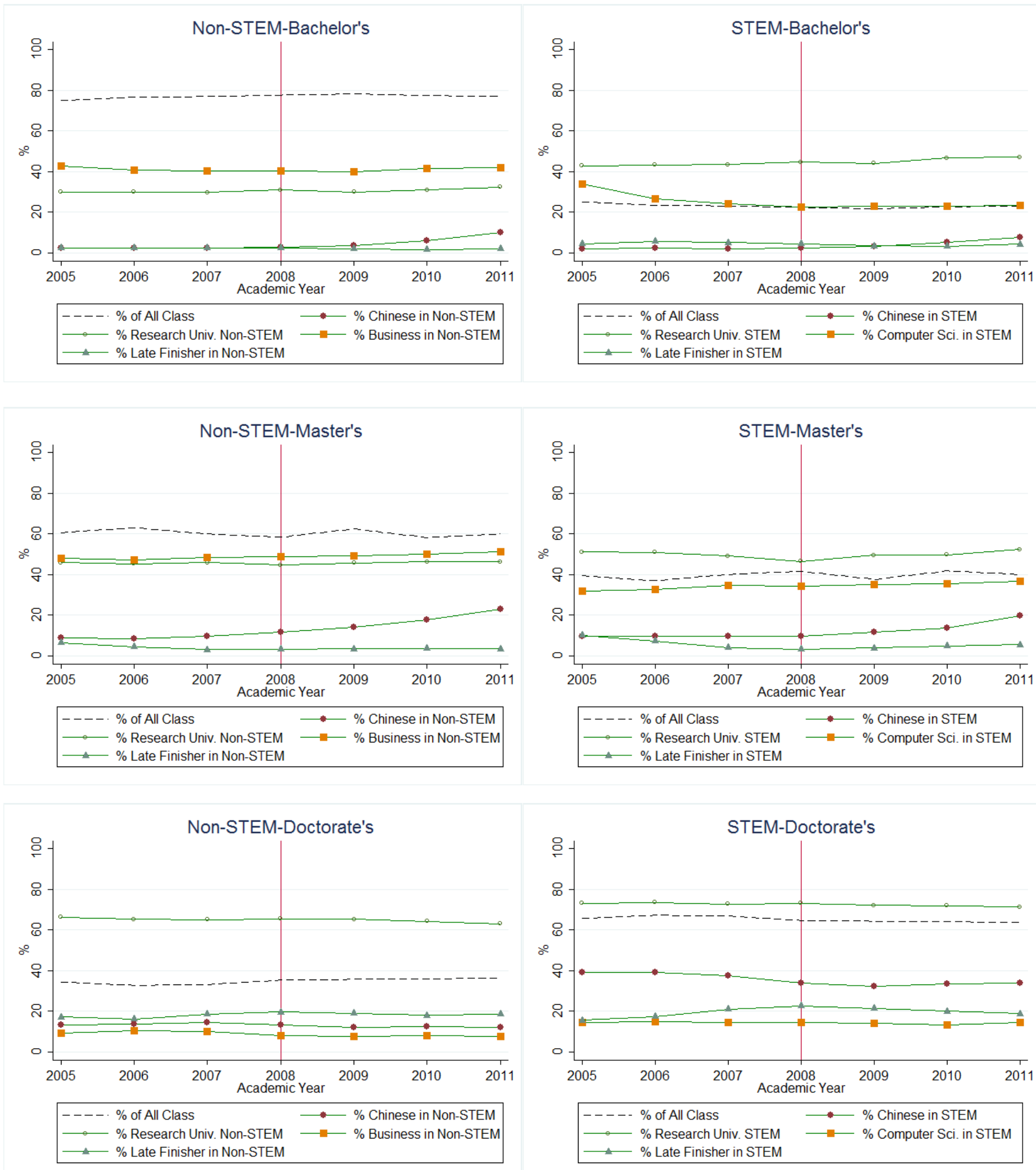
FIGURE A2: THE LABOR MARKET CONDITIONS, STEM VS. NON-STEM FIELDS



Notes: The first panel shows the sum of field-specific GDP in STEM and non-STEM fields, as well as the deviation from their long-run average. The second panel shows the total number of foreign workers hired for STEM and non-STEM occupations under the H-1B visa status along with the percentage of STEM positions among the all hiring. Finally, the last graph shows the relationship between the rise in the unemployment rate from 2008 to 2011 and the percentage of international students in STEM fields within a state. See the appendix for the details in the construction of these variables.

Source: The Bureau of Economic Analysis, the U.S. Department of Labor LCA database, the Bureau of Labor Statistics.

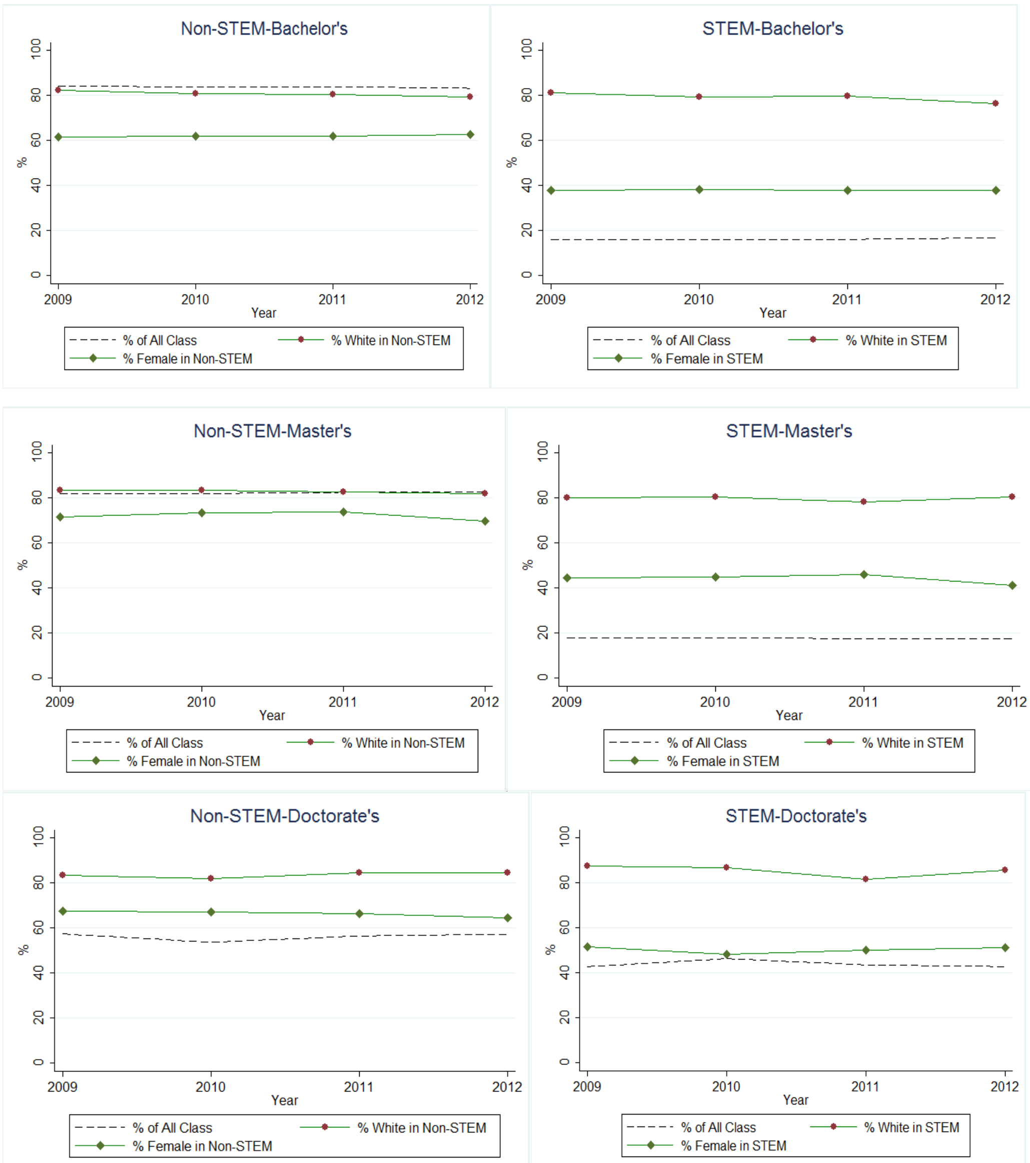
FIGURE A3: THE COMPOSITION OF INTERNATIONAL STUDENTS, BY FIELD AND LEVEL



Notes: The graphs show the percentage of each field within the whole class along with the composition within the field, disaggregated level of study. Research universities comprise of Research I-II and Doctoral I-II of the Carnegie Classification. Late finishers are defined as those who finished studies longer than 6 years at the bachelor's level, 3 years at the master's level, and 6 years at the doctoral level. The vertical line shows the year when the OPT extension policy was enacted.

Source: SEVIS data.

FIGURE A4: THE COMPOSITION OF RECENT NATIVE GRADUATES, BY FIELD AND LEVEL



Notes: The graphs show the percentage of each field within the whole class among recent native graduates along with the composition within the field, disaggregated level of study.

Source: 2009-2012 ACS.

A5. Tables

TABLE A1: THE DATE WHEN THE H-1B VISA CAP WAS REACHED.

Fiscal Year	The Date when the Regular Cap was reached	The Date when the Advanced Degree Cap was reached
2004	October 1,2003	X
2005	October 1,2004	X
2006	August 10, 2005	January 17, 2006
2007	May 26, 2006	July 29, 2006
2008	April 3, 2007	April 30, 2007
2009	April 7, 2008	April 7, 2008
2010	December 21, 2009	August 14, 2009
2011	January 27,2011	January 21, 2011
2012	November 23, 2011	October 19, 2011
2013	June 11, 2012	June 7, 2012
2014	April 7, 2013	April 7, 2013
2015	April 7, 2014	April 7, 2014

Notes: Author's tabulations from the United States Citizenship and Immigration Services' (USCIS) website and related media reports. A fiscal year starts on October 1^{st} of the previous calendar year. The USCIS starts to accept petitions on April 1^{st} for the upcoming fiscal year. The cap for advanced degrees became effective on May 5, 2005, so that the related cells are blank in the table.

TABLE A2: IMPACT OF OPT EXTENSION ON INTERNATIONAL STUDENTS, ROBUSTNESS CHECKS

	Bachelor's Sample			Master's Sample			PhD's Sample		
Dependent Variable:	Initial Stay	Length	18-month	Initial Stay	Length	18-month	Initial Stay	Length	18-month
Baseline Results in Table 3 & 4	0.036***	96.9***	0.12***	0.062***	153.2***	0.27***	0.021***	90.6***	0.11***
	(0.007)	(5.8)	(0.005)	(0.008)	(8.1)	(0.013)	(0.006)	(6.1)	(0.007)
Including those status update before school end	0.014**	97.2***	0.12***	0.060***	153.1***	0.27***	0.0090*	90.7***	0.11***
	(0.007)	(5.83)	(0.005)	(0.007)	(8.13)	(0.013)	(0.006)	(6.17)	(0.006)
Restrictions by Entry Class	0.022***	102.5***	0.13***	0.057***	153.0***	0.27***	0.015**	88.5***	0.091***
	(0.008)	(6.2)	(0.006)	(0.008)	(8.5)	(0.013)	(0.007)	(5.6)	(0.005)
Excluding possible "drop-outs"	0.035***	100.2***	0.13***	0.064***	154.2***	0.27***	0.27***	91.7***	0.11***
	(0.007)	(5.68)	(0.005)	(0.007)	(8.18)	(0.013)	(0.013)	(6.23)	(0.007)
Excluding those started school after policy	0.030***	100.3***	0.12***	0.055***	149.1***	0.26***	0.016***	90.4***	0.11***
	(0.008)	(5.7)	(0.006)	(0.007)	(8.7)	(0.014)	(0.006)	(6.2)	(0.006)
Restricting sample to the Science, Engineering, and Health	0.034***	113.6***	0.12***	0.048***	155.7***	0.22***	0.016**	94.9***	0.091***
	(0.009)	(7.63)	(0.006)	(0.008)	(8.63)	(0.011)	(0.007)	(7.85)	(0.007)

Notes: Each cell is a separate regression. Coefficients are for the binary indicator of the OPT extension. Dependent variables are the likelihood of staying right after graduation, the length of employment, and the likelihood of staying 18 months after having graduated. Robust standard errors clustered at field and year level are reported in parenthesis. Regressions include year, field and school fixed effects and demographic characteristics (age, gender and country of origin fixed effects).

***Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Source: SEVIS data.

TABLE A3: THE IMPACT OF THE OPT EXTENSION ON INTERNATIONAL STUDENTS, DIFFERENCE IN DIFFERENCES, ONLY ELIGIBLE FIELDS WITH STUDENTS FROM TRADE TREATY COUNTRIES

	Bachelor's	Master's	Doctorates
Likelihood of Staying Initially	-0.00054	0.028***	-0.0046
	(0.009)	(0.007)	(0.006)
Conditional Length of Employment	109.7***	151.7***	81.3***
	(10.8)	(10.1)	(9.8)
Length of Employment	137.1***	168.8***	114.7***
	(16.5)	(10.4)	(13.6)
12-Month Stay Rate	0.22***	0.28***	0.22***
	(0.034)	(0.038)	(0.027)
18-Month Stay Rate	0.10***	0.16***	0.050***
	(0.010)	(0.008)	(0.005)
24-Month Stay Rate	0.079***	0.11***	0.031***
	(0.007)	(0.008)	(0.004)

Notes: The sample is restricted to students only in STEM fields eligible for the OPT extension. Each cell is a separate regression. Coefficients are for the interaction of the binary indicator of non-treaty countries of trade agreements, whereas Canada, Mexico, Chile, Singapore, and Australia (after May 11, 2005) compose treaty countries. Robust standard errors clustered at field and year level are reported in parenthesis. Regressions include year, field and school fixed effects and demographic characteristics (age, gender and country of origin fixed effects).

***Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Source: SEVIS data.

TABLE A4: IMPACT OF OPT EXTENSION ON INTERNATIONAL STUDENTS, HETEROGENEITY BY SUBGROUPS, DOCTORATES LEVEL

Dependent Variable:	Initial Stay	Length	18-month stay
By Country of Origin			
China	0.013*	80.3***	0.11***
	(0.007)	(7.1)	(0.008)
India	0.023***	94.9***	0.12***
	(0.007)	(7.0)	(0.008)
Canada	-0.031	95.4***	0.058***
	(0.022)	(13.3)	(0.012)
Europe	0.013	99.0***	0.10***
	(0.011)	(7.9)	(0.009)
Other	0.034***	98.0***	0.10***
	(0.007)	(6.7)	(0.007)
By University Type			
Research	0.019***	86.1***	0.10***
	(0.006)	(6.1)	(0.007)
Master's/Comprehensive	-0.006	123.5***	0.14***
	(0.023)	(14.6)	(0.017)
Baccalaureate & Others	0.028***	101.6***	0.11***
	(0.007)	(6.9)	(0.007)

Notes: See notes to Table 5.

TABLE A5: IMPACT OF FOREIGN STUDENTS ON LABOR MARKET OUTCOMES OF RECENT GRADUATE NATIVES BY GEOGRAPHY, IV ESTIMATES AT THE MASTER'S LEVEL

Dependent Variable:	Employed	FYFT	Log Earnings
Results from Table 9	-0.0032**	-0.0072***	-0.0166***
	(0.0016)	(0.0028)	(0.0040)
States affected more from the Recession	-0.0061***	-0.0068*	-0.0122*
	(0.0017)	(0.0039)	(0.0063)
States affected less from the Recession	0.0005	-0.0085**	-0.0246***
	(0.0032)	(0.0033)	(0.0060)
California (N=1854)	-0.0120***	-0.0132	-0.0041
	(0.0035)	(0.0084)	(0.0144)
Florida (N=990)	-0.0085	-0.0424**	-0.1352***
	(0.0101)	(0.0198)	(0.0353)
New-York (N=2587)	0.0038	-0.0032	-0.0449***
	(0.0031)	(0.0042)	(0.0147)
Massachusetts (N=858)	-0.0087	-0.0175	-0.0324
	(0.0073)	(0.0136)	(0.0221)
Texas (N=1338)	-0.0079**	-0.0205**	-0.0058
	(0.0040)	(0.0087)	(0.0267)

Notes: Each cell is a separate regression with the sample of people in the specified geography. States are classified based on their standing with respect to the median state in terms of the rise in unemployment rate during the recession. Coefficients are for the percentage of F-visa students in each field. See notes to Table 7 for its definition, instrument, and the sample restrictions. Robust standard errors clustered at field and year level are reported in parenthesis. Regressions control for year and field fixed effects, state-level unemployment (in top three rows), and demographics (age, age square, gender, and race/ethnicity). Estimates are weighted with person weights provided by Census.

***Significant at 1%, ** Significant at 5%, * Significant at the 10%.

Source: 2009-2012 ACS.