Does H-1B Visa Reforms Affect Whether US Natives Major in STEM Fields?

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This paper exploits large changes in the H-1B visa program and examines the effect of changes in H-1B admission levels on the likelihood that US natives major in STEM fields. Compare to effect on labor market outcomes, the possible impact of H-1B visa reforms on natives' college major choices indicate effect over longer horizons. I find some evidence that H-1B population adversely affect natives' choices in STEM fields when they enter the college and graduate from it. Female, male and White subgroups have been negatively affected, and the native Asian subgroup suffer from the most dramatic crowd-out effect. Given that the H-1B population share had been more than doubled during 1992 to 2017, the probability of native Asian graduates majoring in STEM fields would be 2.56 percentage points larger, if the H-1B population shares had remained at their 1992 levels and all else had remained the same. Since foreign-born Asian account for a large proportion of H-1B visa holders, there might be an interesting "Asian crowd out Asian" story.

Keywords: H-1B visa program, college major choices, STEM fields, crowding out effect.

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1. Introduction

The number of college students major in STEM (science, technology, engineering and mathematics) fields is commonly viewed as critical to the long-term technology advancement and economic growth of United States. Nowadays, there has been concern that not enough US natives are studying in STEM fields, and one possible reason is that they might be crowded out by foreign-born students. According to the data released by 2009-17 American Community Survey (ACS), the proportion of US natives major in STEM fields varied within the range of 15% to 25% during year 1960 to 2017. It was relatively stable fluctuating around 20% in 1990s and 2000s, and kept increasing after 2010. But the percentage of foreign-born students major in STEM fields has been always higher than that of native graduates, and it showed a nearly 15% increase during 1960 to 2017. Theoretically, large amount of foreign-born students studying STEM majors might be a double-edged sword for native graduates. Foreign-born students could possibly crowd out natives of STEM majors because they are competing for limited education resources, or there might be positive spill-over effect instead when natives are attracted and retained in those fields.

The relationship between natives' college major choices and H-1B visa reforms might be trivial at first glance. But according to the data released by U.S. Citizenship and Immigration Services (USCIS), large proportion of H-1B visa holders work in STEM related occupations. Thus the H-1B visa program governs most admissions of foreign-born graduates with a bachelor's degree or above major in STEM fields for employment in United States. Therefore, whether the large changes in this program will affect US natives' major choices in STEM fields or not becomes an interesting research question to explore.

Since it was created in year 1992, the controversy over H-1B visa program never stops. Proponents emphasize that those high-skilled workers are important to the technology advancement of US economy, and if H-1B visa is contracted, "America is losing many very skilled workers ... They are losing their dreams, and America is losing the value they bring". (Yu (2017)). While the detractors keep worried about native US workers being displaced by foreign-born workers, or furthermore, native US students being crowded out by foreign-born students in especially STEM fields. Compare to the impact on natives' labor market outcomes, possibility of affecting the major choices in STEM fields of native students might be even more worthy of studying, because the effect could be on the US economy operation over longer horizons.

To bring identification to the research question, following Kerr & Lincoln (2010), I will exploit large changes in the H-1B population over the 1992-2017 period. The H-1B population fluctuated substantially during this period because firstly, the national cap on new H-1B issuance varied a lot from a lower bound of 65,000 new workers a year to a higher bound of 195,000. Secondly, the usage of cap and total H-1B issuance also varied a lot due to the change of policy and economic condition. According to the summary statistics published by USCIS, large proportion of H-1B specialty occupation workers are young (between the ages of 25 and 34), well educated (with a bachelor's degree or above), working in STEM-related occupations and earn relatively high median salary.

This study focuses on the relationship between natives' college major choices and H-1B visa reforms. More specifically, I am trying to measure the impact of changes in H-1B population on the probability that US native students choose to major in STEM related fields when they enter the college and graduate from it. I choose the undergraduate level education because this is the key step for an individual to obtain a STEM degree and work in STEM related occupations after graduation. The ACS is a large-scale survey conducted by the U.S. Census Bureau every year and it has asked respondents with at least a bachelor's degree to report their college majors since 2009. Although there are previous literatures looking at the outcomes of H-1B visa program, and literatures focusing on the possible factors that affect students' major choices, to the best of my knowledge, this is the first paper examining the relationship between H-1B visa reforms and US natives' college major choices in STEM fields directly.

More specifically, this paper measures the possible impact of changes in H-1B admission levels on the likelihood that US natives major in STEM fields over the 1992-2017 period. To bring identification of this problem, I exploit the variation of H-1B population shares across areas and over time. This is not easy due to data limitation. Exploiting the variation of H-1B population across more narrowly defined labor markets is difficult with standard data resources. Therefore, I have applied a innovative approach exploiting the micro-level data in the first step of H-1B visa application. Another challenge is to identify the causal relationship, which is also difficult because of the endogeneity of immigrants' self location choices. Hence I have applied an instrumental variable approach constructing an IV based on the historic settlement pattern of foreign-born STEM workers. To better interpret the results, I also take a further look at the impacts on different gender and race subgroups. This is a reasonable approach because different subgroups vary from one to another. According to the data, much less female students choose STEM majors compare to male students, while much more Asian natives choose to major in STEM fields compare to other race groups. Existing literatures also find some heterogeneity among different gender and race subgroups. For example, Griffith (2010) shows that the persistence in STEM majors is much lower for women and minorities. Ost (2010) also find similar results, while Rask (2010) find the opposite. Analyzing the results for different subgroups could reveal a more complete story and help shed light on policy implications. For all of my preferred specifications, I have included control variables of lagged H-1B population, personal characteristics, and labor market conditions. State and year fixed effects and state-specific linear trends are also included to make the causal relationship more valid.

In this paper, I have found significant negative impacts of H-1B population shares on natives majoring in STEM fields, both when they enter the college and graduate from it. For students' beginning their college education, a 10% increase in the H-1B population share decreases the probability of native students choosing STEM majors by 0.032%, decreases the likelihood of a male native student majoring in STEM related fields by 0.07%, and decreases that of a White native student by 0.025%. Given that the H-1B population share had been more than doubled from year 1992 to 2017, the probability of native students majoring in STEM fields when they enter the college would be 0.74 percentage points larger, if the H-1B population shares had remained at their 1992 levels and all else had remained the same. Similarly, the likelihood of male native students choosing STEM majors would be 1.62 percentage points larger, and that of White native students would be 0.58 percentage points larger. For students' graduating from college, results indicate that a 10% increase in the H-1B population share decreases the probability of native graduates choosing STEM majors by 0.021%, decreases the likelihood of a female native graduate majoring in STEM related fields by 0.014%, decreases that of a male native graduate by 0.032%, and decrease that of a White native graduate by 0.02%. The native Asian subgroup suffer from the most dramatic crowd-out effect. A 10% increase in the H-1B population share would decrease the likelihood of an Asian native graduate majoring in STEM related fields by as large as 0.111%. Again, given that the H-1B population share had been more than doubled, the probability of native graduates majoring in STEM fields when they graduate would be 0.49 percentage points larger, the likelihood of female native graduates choosing STEM majors would be 0.32 percentage points larger, that of male native graduates would be 0.74 percentage points larger, and that of White native graduates would be 0.46 percentage points larger. For the native Asian subgroups, the probability would have been as large as 2.56 percentage points larger if the H-1B population shares had remained at their 1992 levels and all else had remained the same. Since foreign-born Asian account for a large proportion of H-1B visa holders, there might be an interesting "Asian crowd out Asian" story here.

The remainder of this paper is organized as follows: The introduction of related works is summarized in Section 2. The background information including the US college major choices and the H-1B visa program, as well as the details of the dataset being used are explained in more details in Section 3 and Section 4 respectively. Section 5 describes the empirical framework in details, including the plain Probit regression model and the instrumental variable approach. Section 6 shows the results of both approaches and Section 7 concludes.

2. Literature Review

Previous literatures mainly focus on the labor market outcomes of H-1B visa program. Lowell (2000), Lowell & Christian (2000), Kirkegaard (2005), and Reksulak et al. (2006) provide some general information about H-1B visa program, H-1B population estimates and characteristics of H-1B visa holders. The evidence of impact of H-1Bs on labor market outcomes are mixed. Some papers find that the H-1B visa holders adversely affect native workers' employment opportunities, wages, etc. For example, Lowell (2001) raise some concern given trends in the postdoctoral labor market and for employers in 'job shops' who undercut US workers with temporary workers. Matloff (2002) criticize that the industry's motivation for hiring H-1Bs is primarily a desire for cheap, compliant labor, and show the adverse impacts of the H-1B program on various segments of the American computer-related labor force. Kirkegaard (2005) find some evidence of aggressive wage-cost cutting, including paying H-1B recipients only the legally mandated 95 percent of the prevailing US wage, among some H-1B employers. In contrast, some other papers show positive impacts of

H-1B workers on natives' earnings, employment rate, etc. For example, Zavodny & VThe (2003) find some positive relationship between LCAs (Labor Condition Applications, the first step towards H-1B visa application) and earnings, earnings growth, and the unemployment rate in the IT sector at the state level. Kerr & Lincoln (2010) show that higher H-1B admissions increase immigrant science and engineering (SE) employment and patenting by inventors with Indian and Chinese names in cities and firms dependent upon the program relative to their peers. Hunt (2011) find that immigrants who entered on a temporary work visa have a large advantage over natives in wages, patenting, and publishing, and are more likely to start companies than similar natives. Peri et al. (2015) show that increases in STEM workers are associated with significant wage gains for college-educated natives, and foreign STEM increased total factor productivity growth in US cities.

Besides the mixed evidence of impacts of H-1B workers on native workers' labor market outcomes, there are also a few studies paying attention to the H-1B visa program on educational outcomes. For example, Kato & Sparber (2013) find that restrictive immigration policy disproportionately discourages high-ability international students from pursuing education in the United States. And Amuedo-Dorantes & Furtado (2019) show that the binding cap of H-1B visa raises international students' likelihood of employment in academia, even outside of their field of study.

With respect to students' college major choices, existing literatures have revealed different factors that might contribute to this decision making process - in STEM or non-STEM fields - and whether students tend to persist or change their majors during college, using both reduced-form and structural model approaches. For example, Bound & Turner (2010) find that the number of foreign PhD students in sciences majors shows a positive effect on undergraduate students also choosing sciences majors. Arcidiacono et al. (2012a) show that academic background can fully account for average differences in switching behavior between blacks and whites. Luppino & Sander (2013) find that weaker, non-minority students typically respond to greater competition in the sciences by shifting their major choice. Orrenius & Zavodny (2015) find some evidence that immigration adversely affects whether US-born women who graduated from college majored in a science or engineering field. Arcidiacono et al. (2016) show significant sorting into majors based on academic preparation, with science majors at each campus having on average stronger credentials than their non-science counterparts. Baird et al. (2016) find that students with relatively greater non-STEM ability are more likely to switch out of STEM. Arcidiacono (2004) estimate a dynamic model of the ability sorting across majors and conclude that virtually all ability sorting is because of preferences for particular majors in college and the workplace. Arcidiacono et al. (2012b) estimate a model of college major choice that incorporates subjective expectations and assessments and show that both expected earnings and students' abilities in the different majors are important determinants of a student's choice of a college major. Altonji et al. (2016) develop a dynamic model of educational decision-making and figure out the important role for heterogeneity in tastes for fields of study and the occupations they lead to.

To summarize, there are previous literatures looking at the outcomes of H-1B visa program, and literatures focusing on the possible factors that affect students' major choices, while to the best of my knowledge, this is the first paper to exam the relationship between H-1B visa reforms and US natives' college major choices in STEM fields directly.

3. U.S. College Major Choices

My paper applied data on college majors from the 2009-17 ACS. The ACS is a large-scale survey conducted by the U.S. Census Bureau every year. Since 2009, it started to ask respondents with at least a bachelor's degree to report their college major. To define STEM majors, the Department of Homeland Security (DHS) has made a STEM Designated Degree Program list, which is a complete list of fields of study that DHS considers to be science, technology, engineering or mathematics (STEM) fields of study for purposes of the 24-month STEM optional practical training extension. According to the regulation, a STEM field of study is a field of study "included in the Department of Education's Classification of Instructional Programs taxonomy within the two-digit series containing engineering, biological sciences, mathematics, and physical sciences, or a related field. In general, related fields will include fields involving research, innovation, or development of new technologies using engineering, mathematics, computer science, or natural sciences (including physical, biological, and agricultural sciences)". Combine the STEM Designated Degree Program list with the field of degree information provided by ACS, I have established a list of STEM majors in appendices Table 7. Compare to the classification in Orrenius & Zavodny (2015), which includes only majors in biology and life sciences, physical sciences, engineering, computer and information sciences, and mathematics and statistics as STEM majors, my classification is broader and fits the STEM optional practical training extension well, which is highly correlated with the H-1B visa program. This broader classification has increased the percentage of STEM majors in my raw data from 19.74% (according to the definition of STEM majors in Orrenius & Zavodny (2015)) to 22.64%.

Assume that the traditional college age is aged 18-22. Figure 1 shows the percentage of US native college graduates who majored in STEM fields when they were age 22, the modal age when they graduated, during year 1960 to 2017, as well as that of foreign-born students. The solid line indicates that the proportion of US natives majoring in STEM fields varied within the range of 15% to 25% during the period. It declined in the 1960s and rose in the 1970s. The increase in the

1970s and early 1980s might reflect the emphasis on science and math during that time (Orrenius & Zavodny (2015)). A sharp decrease occurred in mid-1980s and the ratio went back to around 20% until 2010. It seems that the Internet boom of the late 1990s did not have a significant impact on native students' major choices in STEM fields. The ratio kept increasing after year 2010. Due to the data collecting process, foreign-born students being included in the analysis are those who were living in the United States when the ACS was conducted. The dot line shows that a much higher percentage of foreign-born students choosing to major in STEM related fields compared to native graduates, and the ratio revealed a nearly 15% increase during this period. After the introduction of H-1B visa program since early 1990s, the ratio kept growing when the program expanded and decreased when the policy contracted in early 2000s. After that it began rebounding when the macroeconomy started to recover from the crisis, and the H-1B population also kept growing since then.

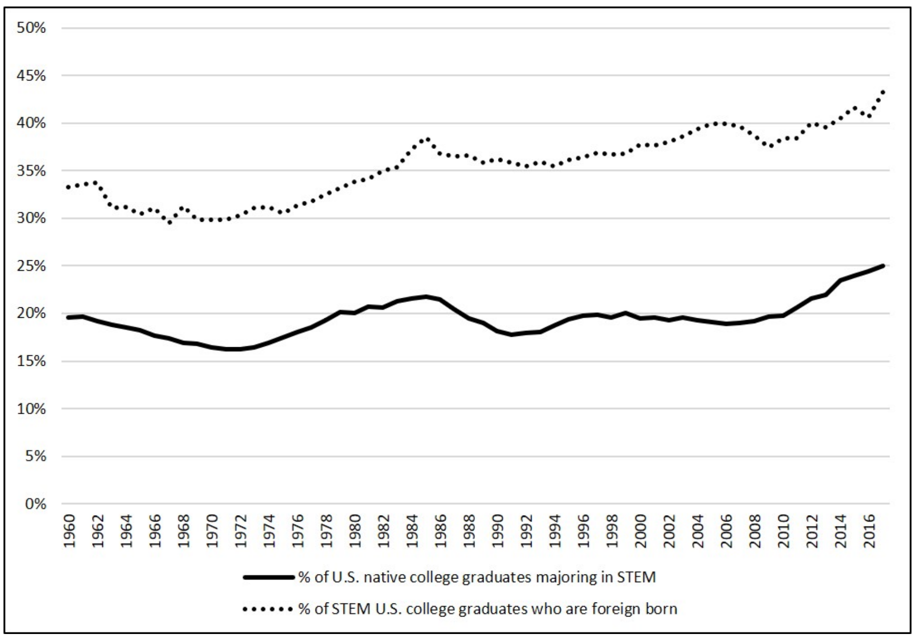

Figure 1 The Proportion of College Graduates Majoring in STEM by Nativity

Figure 2 shows the percentage of US native college graduates majoring in STEM fields by gender group. In general, the proportion of male and female STEM students share similar trends during this time period. The proportion of male students choosing STEM majors is much higher than that of female students, whereas female students showed a more stable increasing trend compared to that of the male students. Figure 3 shows the percentage of US native college graduates majoring in STEM fields by race group. I have divided the native students into four different race groups: non-Hispanic white, non-Hispanic black, Asian and Hispanic. The non-Hispanic other race is not shown. The solid line representing the non-Hispanic white group is smooth with largest number of observations. Dot line for non-Hispanic black group and dash line for Hispanic group show smaller percentages of native students majoring in STEM fields, compared to that of the non-Hispanic white group. The Asian group, represented by the dash dot line, indicates a much higher and more volatile proportion of STEM students compared to all the other three groups.

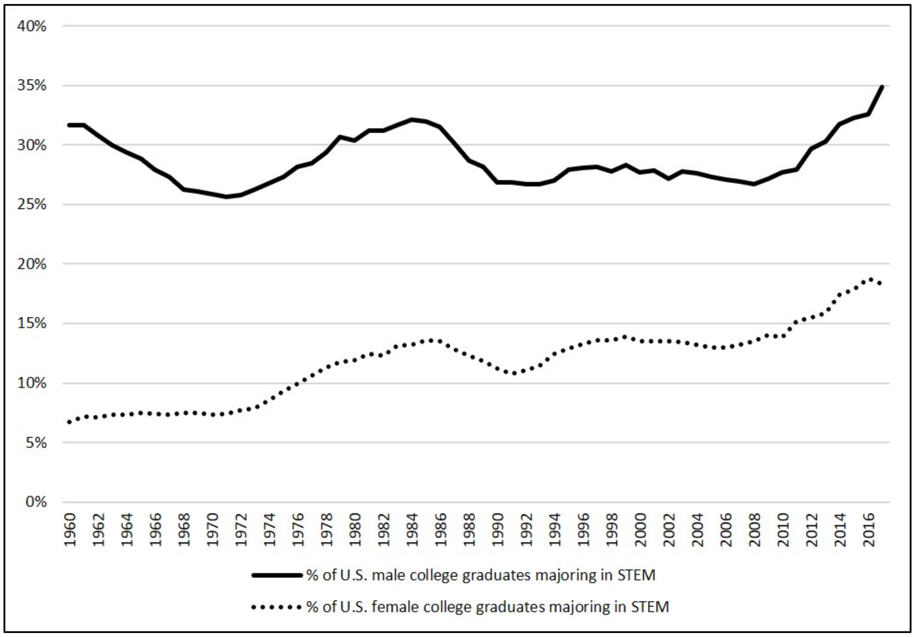

Figure 2 The Proportion of U.S. Native College Graduates Majoring in STEM by Gender

In my empirical analysis, I will match the state-level data of H-1B population with individuals' state of birth. State of birth is the only place of residence available in the ACS besides the current place and place one year ago, and state of birth is also highly correlated with the state of having college education in United States, compared to the other two places. There are also other previous literatures using the state of birth to examine state-level variables related to college education. (Card & Krueger (1992), Dynarski (2008), Bound et al. (2009), Orrenius & Zavodny (2015)) An advantage of using state of birth is to mitigate the endogeneity selection bias that might arise if the H-1B population affects US native college students' location choice of college attendance. According to the data published by National Center for Education Statistics, the average ratio of all first-time degree/certificate-seeking undergraduates in degree-granting postsecondary institutions entering a college within their state of birth was as high as 81.80% in year 1992 (Utah has the highest proportion of 94% and Connecticut has the lowest of 59%, with District of Columbia being excluded) and 78.38% in year 2016 (Utah has the highest proportion of 90.85% and Vermont has the lowest of 50.60%, with District of Columbia being excluded). Figure 4 shows the variation of

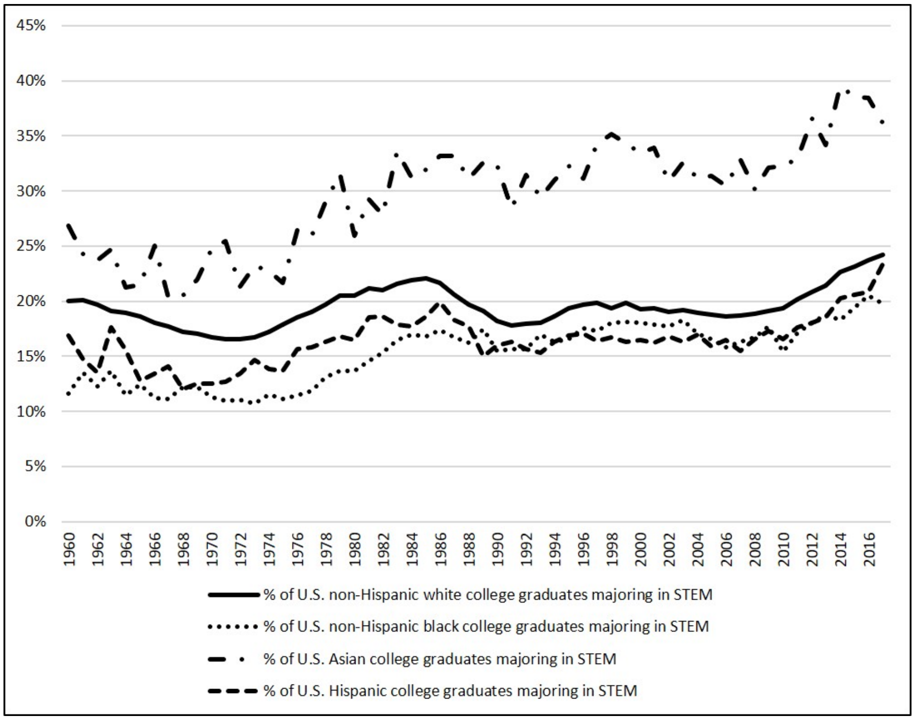

Figure 3 **The Proportion of U.S. Native College Graduates Majoring in STEM by Race**

proportion of in-state students across states when they entered the college in year 1992 and 2016, respectively. From the literature and the data, we should be able to reasonably conclude that state of birth is a good indicator of the state where US natives have their college education. Since not all of the students entering college in their state of birth, my estimates are likely to underestimate the possible impact of H-1B visa reform on US natives' college major choices, and this underestimation would be slightly different across states.

4. H-1B Visa Program

The H-1B is a visa in the United States that allows U.S. employers to temporarily employ foreign workers in specialty occupations. The regulations define a specialty occupation as "requiring theoretical and practical application of a body of highly specialized knowledge in a field of human endeavor including but not limited to biotechnology, chemistry, computing, architecture, engineering, statistics, physical sciences, medicine and health, and requiring the attainment of a bachelor's degree or its equivalent as a minimum" (U.S. Code Title 8, Chapter 12, Subchapter II, Part II, Section 1184 - Admission of nonimmigrants).

Since year 2004, USCIS started to publish the Annual Report to Congress including Report on H-1B Petitions and Characteristics of H-1B Specialty Occupation Workers, both of which provide some summary statistics of H-1B workers. In general, H-1B specialty occupation workers are young

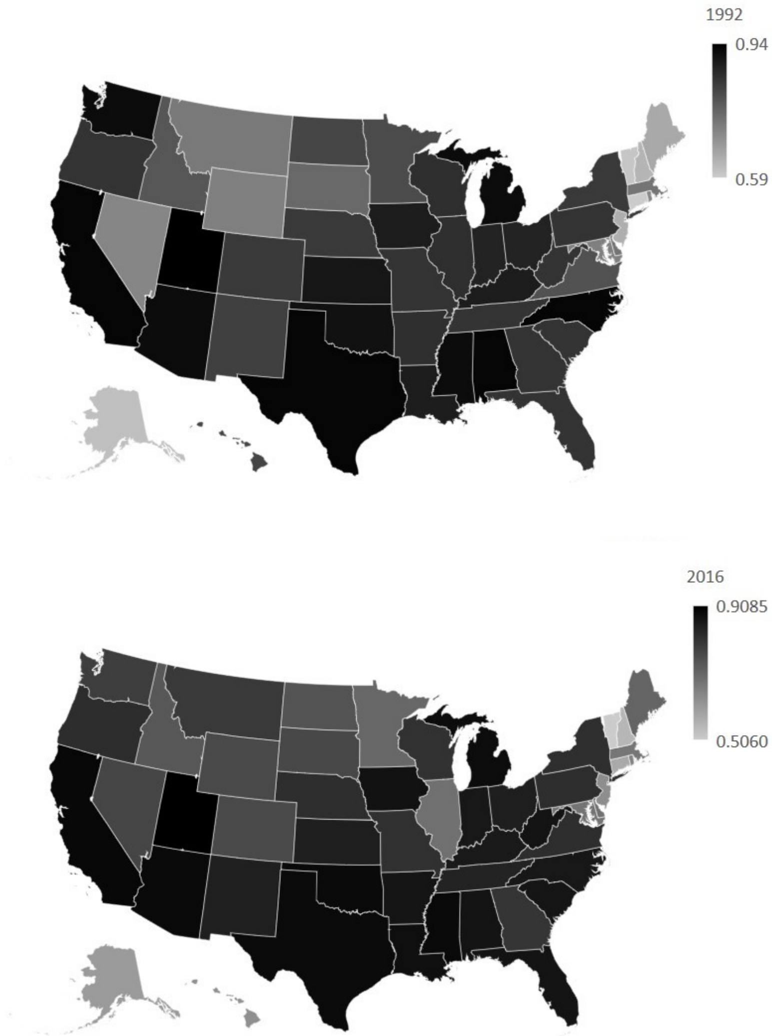

Figure 4 The Variation of Proportion of U.S. Natives Entering College within Their State of Birth across States (year 1992 and 2016, District of Columbia excluded)

(between the ages of 25 and 34) and well educated (with a bachelor's degree or above). More than 80% of those visa holders work in STEM related occupations, such as occupations in computer sciences, engineering, mathematics, physical sciences and life sciences. They also earn much higher median salary compared to the U.S. average. For example, in year 2017, the median salary of beneficiaries of approved H-1B petitions increased to $85,000, much higher than the nominal median income per capita of $31,786 and the real median household income of $61,372 reported by the Census Bureau. More details of the characteristics of H-1B workers are summarized in Table 1.

Because the H-1B visa is a necessity for a foreign-born graduate to work in United States, any reform of it towards to or away from STEM students would reasonably affect foreign-born students'

Table 1 Characteristics of H-1B Specialty Occupation Workers

Year	% age 25-34	% bachelor's degree	% master's degree	% doctorate degree	% computer-related occupations	Median salary
2004	65.5	48.7	33.9	11.2	44.5	$53,000
2005	65.6	44.8	36.8	5.3	43.0	$55,000
2006	66.1	45.0	38.6	10.6	48.4	$60,000
2007	65.7	44.0	40.4	10.1	49.8	$60,000
2008	66.1	43.0	40.6	10.9	49.6	$60,000
2009	65.9	40.9	39.9	12.6	41.6	$64,000
2010	67.7	42.5	39.2	11.7	47.5	$68,000
2011	69.7	41.4	41.7	5.2	50.8	$70,000
2012	72.1	46.3	40.8	8.4	59.5	$70,000
2013	70.9	45.0	41.1	8.8	59.8	$72,000
2014	71.7	45.0	43.1	7.8	64.5	$75,000
2015	71.0	45.0	44.0	7.0	66.5	$79,000
2016	68.9	44.2	45.4	6.9	69.1	$82,000
2017	66.2	45.2	44.5	6.8	69.8	$85,000

major choices in especially STEM fields, and therefore, might crowd US natives out or have positive spillovers on them through attracting or retaining them in those fields.

The H-1B visa program has been changing ever since it started. The Immigration Act of 1990 (implemented in 1992) created the H-1B visa for professional foreign nationals seeking temporary employment in the United States. At the time of its creation, 65,000 H-1B visas became available for new applicants each year. The cap was not reached until fiscal year 1997 and again in 1998. In October 1998, Congress enacted the American Competitiveness and Workforce Improvement Act (ACWIA), which temporarily raised the cap to 115,000 for fiscal years 1999 and 2000. Limit were both reached. Congress responded to the increase in demand for H-1B visas with the American Competitiveness in the 21st Century Act (AC21). The act had two relevant effects. First, it reduced the number of H-1B visas that counted toward the quota by exempting employees of universities, nonprofit research organizations, and governmental research organizations. Second, it raised the cap to 195,000 for each of year 2001, 2002, and 2003. Those limits were never reached. In year 2004, Bachelor's degree cap returned to 65,000 with added 20,000 visas for applicants with U.S. postgraduate degrees. The H-1B cap has been binding every year since then. On April 2, 2008, the U.S. Department of Homeland Security announced a 17-month extension to the OPT for students in qualifying STEM fields. And the 17-month extension has been replaced by a longer 24-month extension since May 10, 2016, which allows the foreign STEM students to work up to 36 months under their student visa, and provides them as long as three years to obtain an H-1B visa.

Figure 5 shows the annual H-1B visa issurance cap (dash line), the H-1B visa issuance for initial employment (dot line), and the H-1B visa population estimate (solid line) during the fiscal year 1992 to 2017. In FY 1999 the actual issuance exceeded the national cap because of a computer malfunction announced by Immigration and Naturalization Service (INS). In recent years, the decoupling of the actual issuances and the numerical cap is due to the policy change that employees working for specific institutions have been exempted from the quota.

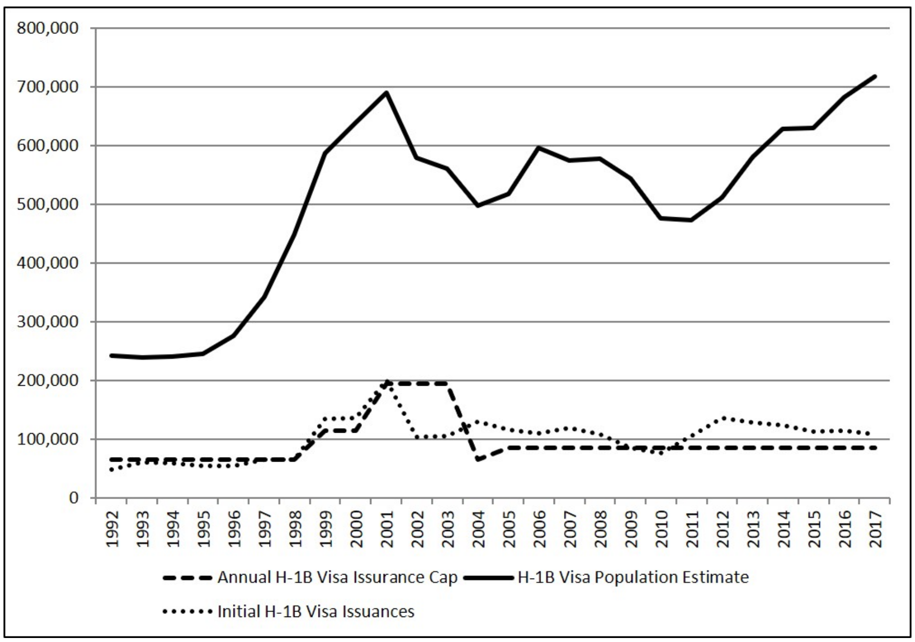

Figure 5 H-1B Visa Issuance and Population Estimates

The solid line in Figure 5 represents an important estimation of H-1B population from FY 1992 to 2017. In this paper, I use the population stock rather than the net issuances or the cap as my primary explanatory variable. Because the change of H-1B population stock reflects not only the change of H-1B inflow but also the outflow, it provides more complete information when we want to see the possible impact of H-1B visa reforms on natives' college major choices. Estimating the H-1B visa population is not straightforward. Although the initial H-1B visa issuance provides a reasonably good measurement of the inflow, the outflow estimation needs to be modeled carefully. Lowell (2000) provides one way to model the outflow of H-1B pool using the information of transitions to permanent residency, emigration, and death. And Kerr & Lincoln (2010) applies Lowell's updated estimates in their 2010 paper. In this study, I will measure the outflow in a more innovative and precise way. Following Costa & Rosenbaum (2017), I assume that the outflow of H-1B pool results not only from people adjusting to lawful permanent resident (LPR) status, emigration and death, but also from some measurement error because of H-1B one-year extensions, possible duplicate petitions, and people changing for employers. Data of adjustment to LPR status come from the yearbook of INS and DHS. Emigration estimations come from Bhaskar et al. (2013) paper. I explore the CDC's (Centers for Disease Control and Prevention) online tool to compute an estimated H-1B mortality rate, as that of Asian and Pacific Islander males between the ages of 25 and 34 by the year 2017. Information of changing employers are from the USCIS yearbook. And according to Costa & Rosenbaum (2017), estimated rate of duplicate petitions approved is around 1% and appoved H-1B one-year extensions estimated by DHS is 18.3%. In Figure 5 we can see that the resulting change in H-1B visa population is large enough to be economically important.

Beyond those nation-level broad statistics, research related to H-1B visa program has been largely restricted by the data limitation. In order to exploit the variation across more narrowly defined labor markets, and control for the many contemporaneous national changes occurring within the United States during the same period, I follow the methodology in Kerr & Lincoln (2010) and exploit the more micro trends using the data of Labor Condition Applications (LCAs) published by U.S. Department of Labor. According to the regulation, for every H-1B petition filed with the USCIS, a LCA must first be certified by the U.S. Department of Labor to ensure that the wage offered to the non-immigrant worker meets or exceeds the "prevailing wage" in the area of employment, so that U.S. workers' wages or working conditions will not be displaced or adversely affected by the foreign workers. A big advantage of LCA data is that it provides much more detailed information of the potential H-1B visa holders, including their work city, county (since 2015) and state since 2001. Although the LCA approvals do not translate one for one into H-1B grants because of the national cap of the H-1B visa issuances, it should be one of the (best) indicators available to shed light on the variation of H-1B population across states.

Since the ACS data only provides state-level information of natives' birthplace, in this paper I will use state as the primary labor market to quantify the possible impact of changing H-1B population on US natives' college major choices in STEM related fields. In order to estimate $\text{H-1B}_{s,t}$, I assume that the variation of H-1B population across states is proportional to the portion of LCAs across states, i.e., $\text{H-1B}_{s,t}$ can be estimated by the following formula,

$$\text{H-1B}_{s,t} = \text{H-1B}_t \cdot \frac{\text{LCA}_{s,t}}{\text{LCA}_t}.$$

Data of $\text{LCA}_{s,t}$ is available since year 2001, thus for year 1992 to 2000, I further assume that the $\text{LCA}_{s,t=1992-2000}$ is equal to the average of $\text{LCA}_{s,t=2001-2017}$.

For every state, I compute the share of H-1B population with respect to state population and rank them according to their "dependency" on H-1B population. Table 2 shows the top 10 and bottom 10 states in year 1992 and 2017 respectively. We can see that there is large variation of H-1B population share across states, ranging from 0.01% (Montana) to 0.34% (District of Columbia, or 0.24% of New Jersey if District of Columbia is excluded) in 1992 and 0.02% (Wyoming) to 0.57% (District of Columbia, or 0.47% of New Jersey if District of Columbia is excluded) in 2017. The standard deviation was as high as 0.06% in 1992 and raised to 0.13% in 2017. The change of H-1B population proportions from 1992 to 2017 reveals that for most of the states, this ratio has been increasing during the time period, with the most dependent states being Washington, California, District of Columbia, New Jersey, and Pennsylvania. Figure 6 also shows the variation of share of H-1B Population across states in year 1992, 2017, and changes from 1992 to 2017 respectively, from the top dependent state to the bottom.

Table 2 **Top 10 Dependent States on H-1B Population in 1992 and 2017**

	1992		2017		change (1992-2017)	
			Top 10 Dependent States			
1	District of Columbia	0.3358%	District of Columbia	0.5732%	Washington	0.3083%
2	New Jersey	0.2425%	New Jersey	0.4658%	California	0.2800%
3	Delaware	0.2249%	Washington	0.4452%	District of Columbia	0.2374%
4	Massachusetts	0.1736%	California	0.4222%	New Jersey	0.2233%
5	Connecticut	0.1572%	Delaware	0.3668%	Pennsylvania	0.1780%
6	California	0.1422%	Massachusetts	0.3511%	Massachusetts	0.1776%
7	Washington	0.1370%	Connecticut	0.2886%	Illinois	0.1682%
8	New York	0.1228%	Illinois	0.2795%	New York	0.1422%
9	Texas	0.1200%	New York	0.2650%	Delaware	0.1419%
10	Georgia	0.1142%	Pennsylvania	0.2617%	Rhode Island	0.1402%
			Bottom 10 Dependent States			
42	Hawaii	0.0269%	Oklahoma	0.0459%	Maine	0.0198%
43	New Mexico	0.0260%	South Dakota	0.0412%	Louisiana	0.0179%
44	Oklahoma	0.0246%	Louisiana	0.0377%	West Virginia	0.0154%
45	Alaska	0.0204%	Alabama	0.0316%	South Dakota	0.0125%
46	Alabama	0.0202%	Montana	0.0308%	Alabama	0.0114%
47	Louisiana	0.0198%	Hawaii	0.0280%	Mississippi	0.0041%
48	Mississippi	0.0166%	West Virginia	0.0277%	Wyoming	0.0026%
49	Wyoming	0.0154%	Mississippi	0.0207%	Hawaii	0.0011%
50	West Virginia	0.0123%	Alaska	0.0196%	Nevada	-0.0002%
51	Montana	0.0110%	Wyoming	0.0180%	Alaska	-0.0007%

5. Empirical Framework

In this paper, I use probit regression model to estimate the possible impact of H-1B visa reforms on US natives' college major choices in STEM related fields. The estimating framework is

$$\text{STEM}_{ist} = I(\alpha + \beta \cdot ln(\text{H-1B Share}_{st}) + \delta X_{ist} + \theta Z_{st} + \phi_s + \eta_t + \varepsilon_{ist} \geq 0),\ \varepsilon \sim (0,1).$$

Assume that traditionally students enter their college in age 18 and graduate in age 22. The dependent variable equals 1 if individual i who was born in state s majored in STEM fields when he or she was 18 or 22 years old in year t. H-1B $\text{Share}_{s,t}$ is the estimated H-1B population in state s and year t as a percentage of the state population in state s and year t. X_{ist} represent the characteristics of individual i, including his or her age, age square, gender, and dummy variables for race (white, black, Hispanic, Asian or other). When these variables are included, they are controlling for any systematic differences in the probability of majoring in STEM fields across different sub-groups. Lagged H-1B population share are also included. For year t when individual was 18 years old, I include lagged H-1B population share for the past 3 years, which should traditionally cover the individual's high school education. Under those specifications, I am trying to measure the possible impact of H-1B visa reforms on US natives' college major choices when they enter the college. And for year t when individual was 22 years old, I include lagged H-1B population share for the past 5 years, which are supposed to cover the individual's college education. Therefore, under those specifications, I am trying to measure the possible impact of H-1B visa reforms on US natives' college major choices when they graduate from college, which is a joint choice of major when they enter and shift during the college.

Intuitively, the condition of STEM jobs market could also affect natives' college major choices in STEM fields. Therefore, Z_{st} represent some specifications controlling for the STEM labor market conditions. I use six different measures to control for the relative attractiveness of STEM jobs, including variables that equal the proportion of college graduates working in STEM occupations in state s and year t, the change of that proportion during the past decade, the ratio of total personal income of college graduates being employed in STEM occupations to that of college graduates in non-STEM occupations in state s and year t, the change of that ratio in the past 10 years, the ratio of wage and salary income of college graduates being employed in STEM occupations to that of college graduates in non-STEM occupations in state s and year t, and the change of that ratio during the past decade. STEM occupations are defined based on the classifications in Peri et al. (2015) paper, data source include 1980, 1990, 2000 census, and 2001 to 2017 ACS. Since the corresponding occupation codes change from dataset to dataset, more details are provided in the Appendices Table 8.

The regression model also includes state and year fixed effects, and state-specific linear time trends. The state-of-birth fixed effects control for any unobservable factors that are specific to the state but constant over time, such as climate and location. The year fixed effects control for any unobservable factors that are specific to that year, such as the macroeconomy condition and policy change. The state-specific linear time trend help control for any unobservable, smooth changes within the state that might affect the likelihood that US natives' college major choices in STEM fields. The standard errors ε_{ist} are robust and clustered on the state.

5.1. Instrumental Variable Approach

The distribution of H-1B population across states might be endogenous, suffering from the problem of self selection. Factors that affect the possibility of H-1B visa holders to live in one certain state might also affect US natives' college major choices in STEM related fields. If those factors could not be completely captured by my labor market control variables, state and year fixed effects, and state-specific linear time trend, the plain Probit regression estimates will have an upward or downward bias. For example, an upward bias might accur if the H-1B visa holders are attracted by a state with educational systems putting more emphasis on STEM education and imposing policies to generate more STEM majors. On the other side, if there are native families who work in STEM occupations and expect their children to also disproportionately major in STEM majors, and decide to move away from the state with a large number of H-1B population before their children are born, this will end up with a downward bias for the plain Probit estimates.

To deal with this potential endogeneity problem, I will apply an instrumental variable approach besides the plain Probit regression model. The instrument is based on the foreign-born STEM workers' historical settlement patterns. Previous studies have found out that immigrants tend to settle in the same areas as earlier immigrants from their country of origin. Existing research using instruments for the immigrant share based on historical settlement patterns include but are not limit to Card & DiNardo (2000), Card (2001), Saiz (2007), Hunt (2017), Smith (2012), etc. According to the summary statistics of the H-1B visa program, we can see that large proportion of H-1B visa holders are working in STEM related occupations. Therefore, the historical settlement patterns of foreign-born STEM workers before the H-1B visa program started might be a good instrument for the distribution of H-1B population nowadays. My instrument variable is constructed by reallocating the H-1B population across states based on the foreign-born STEM workers' distribution, for 17 countries or regions of origin, across states in 1980. The 17 countries or regions are Africa, India, China, Philippines, South Korea, Japan, Rest of Asia, United Kingdom, Germany, France, Rest of Europe, Canada, Mexico, Rest of North America, Oceania, Brazil, and Rest of South America.

These 17 groups are chosen because according to the data provided by Department of State (since 1997) and USCIS (since 2003), each group accounted for a significant share of H-1B visa holders, and each group also accounted for a relatively large share of foreign-born STEM workers in 1980. Therefore, this classification could avoid having large numbers of zeros in my constructed instrumental variables. Recall that year 1980 was more than ten years before the H-1B visa program getting started. Specifically, I compute the predicted H-1B population share in state s and year t according to the following formula,

$$\text{Predicted H-1B Share}_{st} = \frac{\sum_{j=1}^{n} \text{H-1B}_t^j \times \% \text{ of foreign born STEM workers in } s_{1980}^j}{\text{Population}_{st}}.$$

where j represents country or region of origin.

The underlying assumption for this instrument variable to be valid is that the distribution of foreign-born STEM workers by country or region of origin across states in year 1980 is not correlated with any factor that affect US natives' college major choices in STEM related fields occurring more than ten years later. In other words, shocks that affect the distribution of foreign-born STEM workers in 1980 and US natives' college major choices do not persist over time. This should be a reasonable assumption because year 1980 predates much of the beginning of the H-1B visa program.

6. Results

Table 3 and Table 4 show the plain Probit regression results for the correlation between H-1B population shares and US natives' college major choices in STEM fields. And Table 5 and Table **??** report the instrumental variables results. For all the results tables, control variables for personal characteristics and labor market conditions are included, as well as state-of-birth fixed effect, year fixed effect, and state-specific linear trend. Besides the all sample regression, I have also divided the full sample into different sub-groups according to gender and race (White, Black, Hispanic and Asian), in order to see the possible impact of H-1B visa reforms on college major choices of different subgroups. The totals for White, Black, Hispanic and Asian do not sum to the full sample size because otherrace category is not included. As explained in 5, lagged H-1B population shares are also included as control variables. For Table 3 and Table 5, I am trying to measure the possible impact of H-1B visa reforms on US natives' major choices when they enter the college. Therefore, I am looking at the coefficients when individuals are in their age 18, which is assumed to be the traditional year of entering college. Lagged H-1B population shares for the past 3 years are included, which normally cover students' high school education. For Table 4 and Table 6, I am trying to measure the possible impact of H-1B visa reforms on US natives' major choices when they graduate from college. Therefore, I am looking at the coefficients when individuals are in their age 22, which is assumed to be the traditional year of graduation. The major choices observed when they graduate are supposed to be a joint choice of majors when they enter and make possible shift during the college. Lagged H-1B population shares for the past 5 years are included, which usually cover students' college education.

Recall that in a linear regression model, we could directly interpreting the estimated coefficients as the marginal effects. But this is not the case for a probit regression model. In general, we cannot interpret the coefficients from the output of a probit regression model in a standard way. The marginal effects of the regressors refer to how much the conditional probability of the outcome variable changes when we change the value of a regressor, holding all other regressors constant at some values. In particular, the marginal effects depend not only on the regression coefficients, but also on the values of all the other regressors. Therefore, in the probit regression model, there is an additional step of computation required to get the marginal effects once we have computed the probit regression fit. In the result tables below, I have listed both the outputs of the coefficients and the average marginal effects (both with corresponding standard deviations) for the purpose of interpretation. Although these two magnitude are different, their sign and significance level are definitely the same.

6.1. Plain Probit Results

From Table 3 we can see that for the full sample, there is no significant relationship found between H-1B population shares and natives' college major choices in STEM fields when they enter the college at age 18. However, if I divide the full sample into different gender and race subgroups, we can see that there are positive effects showing up for the female and the White subgroups, and negative effect for the Hispanic subgroup. In other words, given the choices made when they enter the college, the likelihood of female and White native students choosing STEM majors have been positively affected by the H-1B population shares, while the Hispanic subgroup have been adversely affected.

Further computation of the average marginal effects provide the information of interpreting the magnitude of the impacts. For example, in my Probit regression model with the log of H-1B population share as the explanatory variable, an estimated average marginal effect of 0.0038 suggests that a 10% increase in the H-1B population share increases the probability of a female native student majoring in STEM fields when she enters the college by 0.038 percentage points. Similarly, an estimated average marginal effect of 0.0045 indicates that a 10% increase in the H-1B population share will raise the likelihood of a White native student choosing STEM majors when entering the college by as much as 0.045 percentage points. And an estimated average marginal effect of -0.0212 suggests that a 10% increase in the H-1B population share decreases the probability of a Hispanic native student majoring in STEM fields by 0.212%.

Table 4 shows the plain Probit regression results when students graduate from college at age 22. We can see that no significant result has been found for the full sample or any gender and race subgroup. Both the crowd-in and crowd-out effects found in subgroups above when students enter the college have disappeared.

6.2. Instrumental Variables Results

Given the analysis in Section 5, we know that endogeneity of self-selection problem might bias the plain Probit results positively or negatively. Therefore, a more preferred specification would be the instrumental variable approach. Besides showing the regression results of the IV approach of the probit model, both Table 5 and Table 6 also display the F-test statistics from the first-stage of each IV regression. All the F-test statistics are well above 10, which indicate that the instrument variable is valid and has a strong first-stage.

Table 5 reports the IV regression results when natives enter the college at their age 18. We can see that the IV estimates are more negative compared to the plain Probit results, which indicate that the coefficients of the plain Probit regression model might suffer from upward bias. From the result table we can see that for the full sample, the H-1B population shares adversely affects natives' college major choices in STEM fields significantly at the 99% confidence interval. A 10% increase in the H-1B population shares decreases the probability of native students majoring in STEM fields when they enter the college by as large as 0.032 percentage points. If we take a further look at the impacts on different subgroups, we can see that both male and the White subgroups have been negatively affected. A 10% increase in the H-1B population share would decrease the likelihood of a male native student choosing STEM majors by 0.07%, and decrease that of a White native student by 0.025%.

The implied marginal effects might be trivial at first glance. But recall that the H-1B population share had increased dramatically during year 1992 to 2017, from 0.0954% in 1992 to 0.2204% in 2017. Given that it had more than doubled during the period, the probability of native students majoring in STEM fields when they enter the college would be 0.74 percentage points larger - a nontrivial difference - if the H-1B population shares had remained at their 1992 levels and all else had remained the same. Similarly, the likelihood of male native students choosing STEM majors would be 1.62 percentage points larger, and that of White native students would be 0.58 percentage points larger.

The crowd-out effect remains for the whole sample as well as the male and White subgroups when natives graduate, and even the female and Asian subgroups are adversely affected now. Compare to their major choices when entering the college, students might have a better understanding of the job market they are facing and the career path they are planning when graduation. Therefore, students might choose to change their college majors by shifting to other fields during college education. The final decisions observed in the data show negative estimates for both the full sample and different subgroups. From Table 6 we can see that for the full sample, the H-1B population share adversely affects natives' college major choices in STEM fields significantly when they graduate. Referring to the magnitude, a 10% increase in the H-1B population share decreases the probability of natives choosing STEM fields when graduate by as large as 0.021 percentage points. When we take a further look at the possible impacts on different gender and race subgroups, we can see that more subgroups have been negatively affected. Female, male, White and Asian subgroups have all been adversely affected by the H-1B population share. A 10% increase in the H-1B population share could decrease the likelihood of a female native graduate majoring in STEM fields by 0.014%, decrease that of a male native graduate by a more significant impact of 0.032%, and decrease that of a White native graduate by 0.02%. The native Asian subgroup suffer from the most dramatic negative effect. The parameter estimate indicates that a 10% increase in the H-1B population share would decrease the likelihood of an Asian native graduate choosing STEM majors by as large as 0.111%.

Similarly, given that the H-1B population share had been more than doubled during year 1992 to 2017, the probability of native students majoring in STEM fields when they graduate from college would be 0.49 percentage points larger, if the H-1B population shares had remained at their 1992 levels and all else had remained the same. The likelihood of female native students choosing STEM majors when graduation would be 0.32 percentage points larger, that of male native students would be 0.74 percentage points larger, and that of White native students would be 0.46 percentage points larger. For the native Asian subgroups, the probability would have been as large as 2.56 percentage points larger if the H-1B population shares had remained at their 1992 levels and all else had remained the same. This is a dramatic difference, and since foreign-born Asian account for a large proportion of H-1B visa holders, there might be an interesting "Asian crowd out Asian" story here that is worthy more future works.

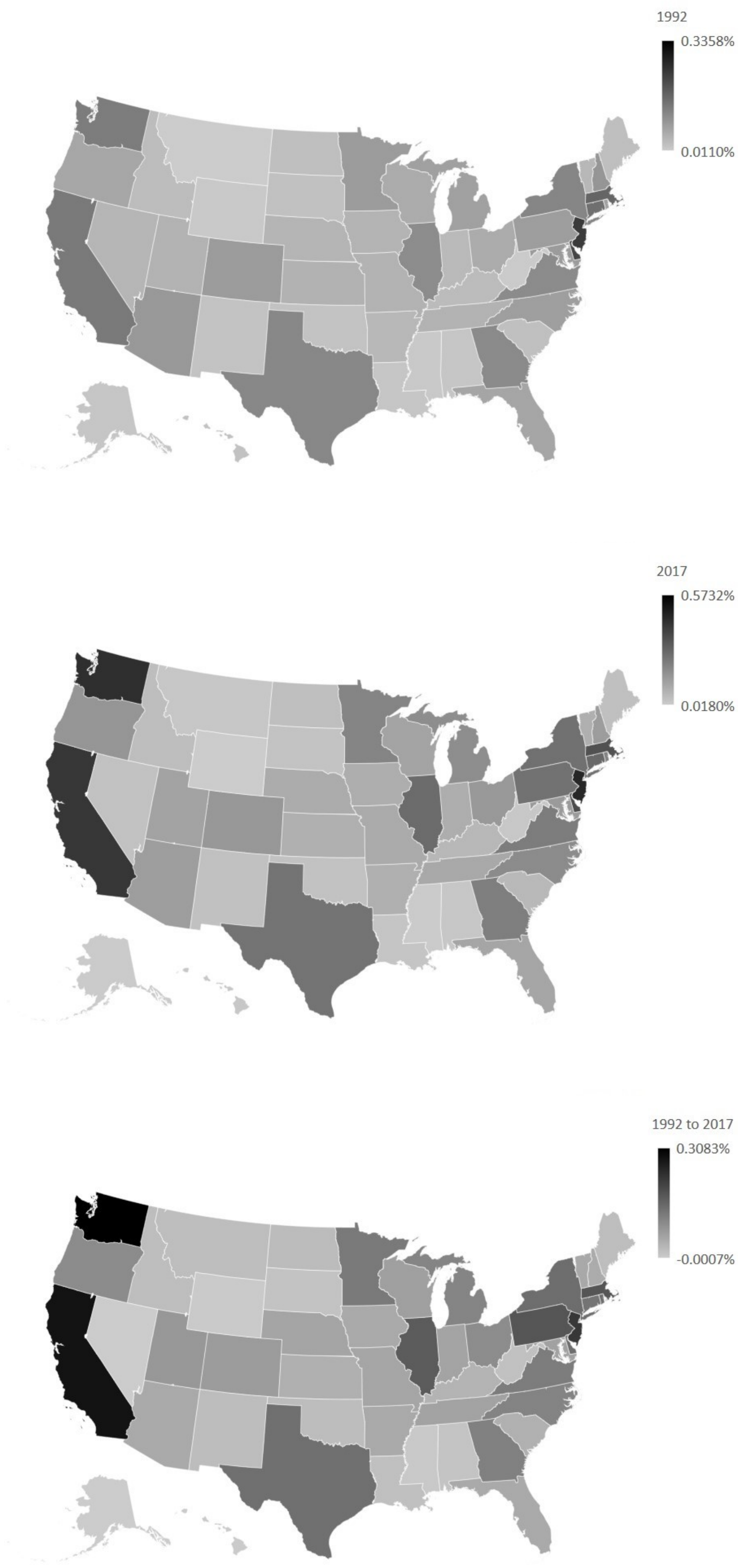

Figure 6 **Distribution of Share of H-1B Population across States in 1992 and 2017**

Table 3 **Probit Regression Estimates for Relationship between Majoring in STEM and H-1B Population Share When Entering College**

% of H-1B population in:	All	Female	Male	White	Black	Hispanic	Asian
Coefficients:							
Age 18	0.0092	0.0171**	0.0004	0.0166**	0.0197	-0.0854**	0.0178
	(0.0070)	(0.0087)	(0.0111)	(0.0070)	(0.0360)	(0.0380)	(0.0310)
Age 17	0.0016	0.0071	-0.0053	0.0012	0.0248	-0.0060	-0.0345
	(0.0091)	(0.0105)	(0.0122)	(0.0096)	(0.0330)	(0.0367)	(0.0483)
Age 16	-0.0092	-0.0078	-0.0112	-0.0070	-0.0143	-0.0194	-0.0419
	(0.0081)	(0.0114)	(0.0120)	(0.0101)	(0.0397)	(0.0454)	(0.0404)
Age 15	-0.0016	-0.0106	0.0064	-0.0021	0.0543*	-0.0317	0.0224
	(0.0088)	(0.0098)	(0.0145)	(0.0093)	(0.0314)	(0.0375)	(0.0406)
Average marginal effects:							
Age 18	0.0025	0.0038**	0.0001	0.0045**	0.0050	-0.0212**	0.0064
	(0.0019)	(0.0019)	(0.0038)	(0.0019)	(0.0091)	(0.0094)	(0.0111)
Age 17	0.0004	0.0016	-0.0018	0.0003	0.0063	-0.0015	-0.0123
	(0.0025)	(0.0024)	(0.0041)	(0.0026)	(0.0083)	(0.0091)	(0.0173)
Age 16	-0.0025	-0.0017	-0.0038	-0.0019	-0.0036	-0.0048	-0.0150
	(0.0022)	(0.0025)	(0.0041)	(0.0027)	(0.0100)	(0.0112)	(0.0145)
Age 15	-0.0004	-0.0024	0.0022	-0.0006	0.0137*	-0.0078	0.0080
	(0.0024)	(0.0022)	(0.0049)	(0.0025)	(0.0079)	(0.0093)	(0.0145)
# of obs	1,373,608	784,689	588,919	1,101,135	85,070	94,601	56,343

Table 4 **Probit Regression Estimates for Relationship between Majoring in STEM and H-1B Population Share When Graduation**

% of H-1B population in:	All	Female	Male	White	Black	Hispanic	Asian
Coefficients:							
Age 22	-0.0127	-0.0097	-0.0163	-0.0134	0.0344	-0.0290	-0.0569
	(0.0097)	(0.0096)	(0.0129)	(0.0089)	(0.0265)	(0.0350)	(0.0469)
Age 21	-0.0093	-0.0022	-0.0163	-0.0091	-0.0538**	0.0231	0.0200
	(0.0082)	(0.0098)	(0.0109)	(0.0089)	(0.0259)	(0.0303)	(0.0444)
Age 20	0.0056	0.0025	0.0086	0.0079	0.0320	-0.0603	-0.0131
	(0.0090)	(0.0104)	(0.0116)	(0.0100)	(0.0359)	(0.0376)	(0.0361)
Age 19	-0.0174**	-0.0157	-0.0192*	-0.0187**	-0.0134	0.0264	-0.0499*
	(0.0087)	(0.0106)	(0.0106)	(0.0090)	(0.0397)	(0.0339)	(0.0292)
Age 18	0.0091	0.0176*	-0.0008	0.0155**	0.0309	-0.0886***	0.0186
	(0.0066)	(0.0095)	(0.0109)	(0.0071)	(0.0332)	(0.0313)	(0.0355)
Average marginal effects:							
Age 22	-0.0035	-0.0022	-0.0055	-0.0036	0.0087	-0.0072	-0.0203
	(0.0026)	(0.0021)	(0.0044)	(0.0024)	(0.0067)	(0.0086)	(0.0168)
Age 21	-0.0025	-0.0005	-0.0055	-0.0025	-0.0136**	0.0057	0.0072
	(0.0022)	(0.0022)	(0.0037)	(0.0024)	(0.0065)	(0.0075)	(0.0159)
Age 20	0.0015	0.0005	0.0029	0.0022	0.0081	-0.0149	-0.0047
	(0.0025)	(0.0023)	(0.0039)	(0.0027)	(0.0091)	(0.0093)	(0.0129)
Age 19	-0.0047**	-0.0035	-0.0065*	-0.0051**	-0.0034	0.0065	-0.0178*
	(0.0024)	(0.0024)	(0.0036)	(0.0024)	(0.0100)	(0.0084)	(0.0104)
Age 18	0.0025	0.0039*	-0.0003	0.0042**	0.0078	-0.0218***	0.0067
	(0.0018)	(0.0021)	(0.0037)	(0.0019)	(0.0084)	(0.0077)	(0.0127)
# of obs	1,627,098	925,293	701,805	1,312,411	102,196	108,507	61,990

Table 5 **IV Regression Estimates for Relationship between Majoring in STEM and H-1B Population Share When Entering College**

% of H-1B population in:	All	Female	Male	White	Black	Hispanic	Asian
Coefficients:							
Age 18	-0.1102***	-0.0443	-0.1917***	-0.0865*	-0.1403	-0.1569	-0.2349
	(0.0421)	(0.0654)	(0.0509)	(0.0481)	(0.1110)	(0.1225)	(0.2016)
Age 17	0.0381**	0.0260	0.0526***	0.0309*	0.0936*	0.0222	0.0609
	(0.0162)	(0.0231)	(0.0202)	(0.0167)	(0.0544)	(0.0595)	(0.0860)
Age 16	-0.0090	-0.0078	-0.0104	-0.0068	-0.0268	-0.0172	-0.0253
	(0.0104)	(0.0114)	(0.0168)	(0.0114)	(0.0482)	(0.0469)	(0.0462)
Age 15	-0.0108	-0.0151	-0.0092	-0.0104	0.0525	-0.0386	-0.0042
	(0.0110)	(0.0108)	(0.0174)	(0.0114)	(0.0337)	(0.0398)	(0.0477)
F-test	22.84	22.77	22.83	20.10	29.10	16.21	25.95
Average marginal effects:							
Age 18	-0.0032***	-0.0010	-0.0070***	-0.0025*	-0.0063	-0.0033	-0.0105
Age 17	0.0011**	0.0006	0.0019***	0.0009*	0.0042*	0.0005	0.0027
Age 16	-0.0003	-0.0002	-0.0004	-0.0002	-0.0012	-0.0004	-0.0011
Age 15	-0.0003	-0.0003	-0.0003	-0.0003	0.0024	-0.0008	-0.0002
# of obs	1,373,608	784,689	588,919	1,101,135	85,070	94,601	56,343

Table 6 IV Regression Estimates for Relationship between Majoring in STEM and H-1B Population Share When Graduation

% of H-1B population in:	All	Female	Male	White	Black	Hispanic	Asian
Coefficients:							
Age 22	-0.1636**	-0.1434*	-0.1952***	-0.1626**	0.0869	-0.1309	-0.7518**
	(0.0638)	(0.0861)	(0.0745)	(0.0682)	(0.1703)	(0.2260)	(0.3117)
Age 21	0.0445	0.0458	0.0468	0.0417	-0.0801	0.0649	0.3316**
	(0.0272)	(0.0348)	(0.0306)	(0.0275)	(0.0859)	(0.0924)	(0.1587)
Age 20	0.0115	0.0073	0.0161	0.0138	0.0349	-0.0552	0.0468
	(0.0110)	(0.0114)	(0.0144)	(0.0121)	(0.0407)	(0.0417)	(0.0434)
Age 19	-0.0248**	-0.0219*	-0.0289**	-0.0269**	-0.0152	0.0207	-0.0900
	(0.0108)	(0.0118)	(0.0135)	(0.0111)	(0.0429)	(0.0439)	(0.0551)
Age 18	0.0039	0.0130	-0.0067	0.0100	0.0358	-0.0872***	-0.0115
	(0.0088)	(0.0115)	(0.0124)	(0.0104)	(0.0358)	(0.0329)	(0.0395)
F-test	18.80	18.14	19.62	17.64	19.01	11.96	19.85
Average marginal effects:							
Age 22	-0.0021**	-0.0014*	-0.0032***	-0.0020**	0.0015	-0.0017	-0.0111**
Age 21	0.0006	0.0005	0.0008	0.0005	-0.0013	0.0008	0.0049**
Age 20	0.0001	0.0001	0.0003	0.0002	0.0006	-0.0007	0.0007
Age 19	-0.0003**	-0.0002*	-0.0005**	-0.0003**	-0.0003	0.0003	-0.0013
Age 18	0.0001	0.0001	-0.0001	0.0001	0.0006	-0.0011***	-0.0002
# of obs	1,627,098	925,293	701,805	1,312,411	102,196	108,507	61,990

7. Conclusion

This paper measures the possible impacts of H-1B visa reforms on US natives' college major choices in STEM related fields. In this study I have built a bridge between H-1B visa program related literatures and college major choices related literatures. Given the endogeneity problem of self-selection, I have constructed an instrumental variable of H-1B population share based on historical settlement pattern of foreign-born STEM workers. I find significant negative impacts of H-1B population shares on natives majoring in STEM fields, both when they enter the college and graduate from it. For students' beginning their college education, a 10% increase in the H-1B population share decreases the probability of native students choosing STEM majors by 0.032%. If we take a further look at different gender and race subgroups, a 10% increase in the H-1B population share could decrease the likelihood of a male native student majoring in STEM related fields by 0.07%, and decrease that of a White native student by 0.025%. Given that the H-1B population share had been more than doubled from year 1992 to 2017, the probability of native students majoring in STEM fields when they enter the college would be 0.74 percentage points larger, if the H-1B population shares had remained at their 1992 levels and all else had remained the same. Similarly, the likelihood of male native students choosing STEM majors would be 1.62 percentage points larger, and that of White native students would be 0.58 percentage points larger.

For students' graduating from college, their reported majors are a joint choice of entering and shifting during college. Results indicate that a 10% increase in the H-1B population share decreases the probability of native graduates choosing STEM majors by 0.021%. When we take a further look at different subgroups, a 10% increase in the H-1B population share could decrease the likelihood of a female native graduate majoring in STEM related fields by 0.014%, decrease that of a male native graduate by 0.032%, and decrease that of a White native graduate by 0.02%. The native Asian subgroup suffer from the most dramatic crowd-out effect. A 10% increase in the H-1B population share could decrease the likelihood of an Asian native graduate majoring in STEM related fields by as large as 0.111%. Again, given that the H-1B population share had been more than doubled, the probability of native graduates majoring in STEM fields when they graduate would be 0.49 percentage points larger, if the H-1B population shares had remained at their 1992 levels and all else had remained the same. Similarly, the likelihood of female native graduates choosing STEM majors would be 0.32 percentage points larger, that of male native graduates would be 0.74 percentage points larger, and that of White native graduates would be 0.46 percentage points larger. For the native Asian subgroups, the probability would have been as large as 2.56 percentage points larger if the H-1B population shares had remained at their 1992 levels and all else had remained the same. Since foreign-born Asian account for a large proportion of H-1B visa holders, there might be an interesting "Asian crowd out Asian" story here.

Appendices

Table 7 STEM Major Classifications

ACS Code	Major Name
1103	Animal Sciences
1104	Food Science
1105	Plant Science and Agronomy
1106	Soil Science
1301	Environmental Science
2001	Communication Technologies
21XX	Computer and Information Sciences
24XX	Engineering
25XX	Engineering Technologies
36XX	Biology and Life Sciences
37XX	Mathematics and Statistics
3801	Military Technologies
4002	Nutrition Sciences
4005	Mathematics and Computer Science
4006	Cognitive Science and Biopsychology
50XX	Physical Sciences
5102	Nuclear, Industrial Radiology, and Biological Technologies
5206	Social Psychology
6105	Medical Technologies Technicians
6108	Pharmacy, Pharmaceutical Sciences, and Administration
6202	Actuarial Science

Table 8 STEM Occupation Classifications

Occupation	Occupation Codes 1980/90 census	2000 census	2001-2009 ACS	2010-2017 ACS
Actuaries	66	120	1200	1200
Aerospace engineers	44	132	1320	1320
Agricultural and food scientists	77	160	1600	1600
Airplane pilots and navigators	226	903	9030	9030
Atmospheric and space scientists	74	171	1710	1710
Biological scientists	78	161	1610	1610
Biological technicians	223	191	1910	1910
Chemical engineers	48	135	1350	1350
Chemical technicians	224	192	1920	1920
Chemists	73	172	1720	1720
Civil engineers	53	136	1360	1360
Clinical laboratory technologies and technicians	203	330	3300	3300
Computer software developers	229	102	1020	1020
Computer systems analysts and computer scientists	64	100	1000	1006
Dentists	85	301	3010	3010
Dietitians and nutritionists	97	303	3030	3030
Electrical engineers	55	141	1410	1410
Geologists	75	193	1930	1930
Industrial engineers	56	143	1430	1430
Management analysts	26	71	710	710
Mathematicians and mathematical scientists	68	124	1240	1240
Mechanical engineers	57	146	1460	1460
Medical scientists	83	165	1650	1650
Metallurgical and materials engineers, variously phrased	45	145	1450	1450
Not-elsewhere-classified engineers	59	153	1530	1530
Occupational therapists	99	315	3150	3150
Optometrists	87	304	3040	3040
Other health and therapy	89	326	3260	3260
Petroleum, mining, and geological engineers	47	152	1520	1520
Pharmacists	96	305	3050	3050
Physical scientists, n.e.c.	76	176	1760	1760
Physical therapists	103	316	3160	3160
Physicians	84	306	3060	3060
Physicians' assistants	106	311	3110	3110
Physicists and astronomers	69	170	1700	1700
Podiatrists	88	312	3120	3120
Psychologists	167	182	1820	1820
Sales engineers	258	493	4930	4930
Social scientists, n.e.c.	169	186	1860	1860
Speech therapists	104	323	3230	3230
Subject instructors (high school/college)	154	220	2200	2200
Therapists, n.e.c.	105	324	3240	3245
Veterinarians	86	325	3250	3250
Vocational and educational counselors	163	200	2000	2000

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