THREE ESSAYS ON THE CHOICE OF COLLEGE MAJOR AND TRADE EXPOSURE

By

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ABSTRACT

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This dissertation is composed of three chapters on the effects of import exposure. For my dissertation I mainly use the variation of import competition across local labor markets to explore its impact on labor market outcomes (e.g., wages and employment status), human capital investment decisions (choice of college major), and education-job mismatch.

Chapter one explores the relationship between increasingly intense Chinese import competition and American college students' choice of major in the 2000s. By employing a modified version of the measure for Chinese import competition from Autor, Dorn, and G. Hanson (2013) and analyzing the relationship between industries and college majors, I find that rising Chinese trade exposure of nineteen industries in the 2000s has a negative effect on American students' choice of six engineering majors. The magnitudes of the effects range from 0.62 to 0.69 percentage point decreases in the probability of choosing those six engineering majors. I also find that males are more negatively affected by Chinese import competition in terms of the choice of the six engineering majors, whereas no significant results exist if I restrict my sample to females.

Chapter two analyzes how increased trade exposure affects students' choice of STEM major. I first present a simple model to illustrate how trade exposure impacts students' utility functions through their self-beliefs about labor market outcomes and then use assorted data to show that import competition positively affects the choice of STEM major. I find that increased import exposure in the 2000s leads to 1.05 and 0.72 percentage point increases in the probability of choosing STEM majors for college underclassmen and upperclassmen, respectively. As for labor market outcomes, my results suggest that a rise in import competition leads to a pronounced negative effect on weekly wages, employment status, and full-time employment across STEM and non-STEM occupations from the late 1990s through the 2000s. STEM occupations, however, are less negatively impacted

by import competition, which helps explain why a rise in import exposure increases the probability of students choosing STEM majors.

Chapter three investigates the impact of import exposure on education-occupation mismatch. I first use the concept of a matching function to explain the connection between mismatch and the supply of and demand for college graduates. Next, I use an input-output table to construct a measure of import exposure that accounts for both direct and indirect trade shocks. Findings show that increased import exposure leads to a rise in education-occupation mismatch from 2011 through 2019. Moreover, for the supply side I present that a rise in import exposure significantly increases the number of bachelor's degrees awarded in 4-year colleges and in most degree fields. However, for the demand side, I do not observe corresponding increases in occupational employment for most fields of education. The unbalanced demand for and supply of college graduates might potentially explain the rise in education-occupation mismatch.

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CHAPTER 1

THE EFFECT OF IMPORT COMPETITION ON AMERICAN STUDENTS' CHOICE OF ENGINEERING MAJOR

1.1 Introduction

Import competition from foreign countries has grown significantly over the past 20 years. This import shock not only directly impacts the manufacturing industries (tradable sector), but also indirectly affects the service industries (non-tradable sector) through a variety of channels (wages and employment). Acemoglu et al. (2016) find that Chinese import competition causes U.S. manufacturing industries to incur a substantial loss of jobs.[1] The influence of Chinese products, however, is not restricted to labor market outcomes. The impact also spills over to people's decision-making process of human capital investment (Blanchard and Olney 2017; Greenland and Lopresti 2016).

I therefore turn my attention to American students' choice of college major, which is an important phase for accumulating one's long-term human capital. As pointed out in the related literature, expected earnings and employment opportunities are both crucial factors in students' decisions on college majors (Berger 1988; Montmarquette et al. 2002). Additionally, people usually choose jobs at least somewhat related to their majors (Robst 2007a). If import competition from foreign countries does affect wages and employment of the U.S. manufacturing sector, then these effects may change students' expectations of employment opportunities or expected earnings of certain majors. Changes in students' expectations can then further influence their willingness to choose the affected majors. For example, we observe a certain proportion of American college graduates in mechanical engineering enter the automobile industry every year even though the automotive industry in Michigan has suffered a continuous decline due to foreign import competition. Will

[1]According to some recent literature, the impact from Chinese import competition is not as large and negative as pointed out by older literature. For example, Feenstra and Sasahara (2018) finds that job losses due to Chinese imports are significantly canceled out by the U.S. export expansion. Bloom et al. (2019) also note that the negative impact of Chinese imports vanishes after 2007.

a contraction of the U.S. auto industry affect college students' willingness to choose mechanical engineering? Students may, instead, choose other majors in which most graduates work in industries that are less affected. They also could still choose mechanical engineering because the demand for high-skilled workers, like college graduates, is still increasing.

This chapter explores the relationship between increasingly intense import competition from China and U.S. college students' choice of college major in the 2000s. There are two reasons why I choose China as the main source of import competition. First, the negative effect of Chinese import competition on the U.S. manufacturing sector has become a stylized fact according to the results derived by previous literature. The dwindling performance of this sector due to the rising productivity of Chinese industries could be the channel through which Chinese import competition affects students' major choices. Second, competition between China and the United States has come into the spotlight in recent years. China as a leading developing country can also be a key indicator of how developing countries impact the U.S.[2] Whether the trade shock from China affects students' willingness to study the engineering field is a crucial question, since sustainable growth of the U.S. economy heavily relies on the abundant talents in science and engineering (S&E) fields.

In this study I use the Public Use of Micro Sample (PUMS) of American Community Survey (ACS) as my main data source and employ a modified version of the measure of Chinese import competition in Autor, Dorn, and G. Hanson (2013). I use instrumental variables to address the potential endogeneity in my econometric model and also use the predicted imports from the gravity model for further robustness check. My results suggest that Chinese trade exposure has a negative effect on American students' choice of six engineering majors. The magnitudes of the effects range from 0.62 to 0.69 percentage point decreases in the probability of choosing the six engineering majors. The effect is much larger and statistically significant for males in the sample but not for females. For males, the magnitudes of the effects range from 1.39 to 1.58 percentage point decreases in the probability. My main results hold firmly after adding assorted state-level controls. This paper contributes to the existing literature by directly exploring the relationship between import

[2] In the appendix, I also explore the effects of import competition from different countries based on their income levels. Please see the results in Table A.3.

competition and choice of college major. Moreover, my findings seek to enrich the literature on human capital investment by recognizing a new source (import competition) that could influence people's decisions on human capital accumulation (major choice).

1.2 Literature Review

A large strand of the literature studies the phenomenon that people with degrees in different fields have quite different earnings. Their results suggest that students with certain college majors can enjoy much higher returns when they enter the job market or people consider these majors to be worth more on the market. Rumberger (1984) finds that college graduates who hold degrees in technical areas (business, physical sciences, health professions, engineering, mathematics, and law) tend to have higher earnings than people with degrees in other fields. Similarly, James et al. (1989) show that students who major in business and engineering tend to enjoy higher returns compared with other majors like education. Rumberger and Thomas (1993) also note that college major still plays a critical role in college graduates' initial earnings after controlling for key factors of determining initial earnings of college graduates (school quality and performance in college).

Following the results of previous empirical papers, it is reasonable to infer that the choice of college major is likely a function of expected future earnings. Berger (1988) builds a conditional logit model of major choice that takes expected future earnings of college majors into account. His empirical study shows that an increase in the present value of future earnings streams of one major raises the probability of choosing the major relative to others.[3] However, instead of using future earnings stream, Montmarquette et al. (2002) model the choice of college major by using expected earnings as the central determinant.[4] Using the NLSY dataset, they find that the expected earnings variable still significantly affects choice of college major even after controlling for family background and socioeconomic status. Aside from expected earnings or future earnings stream, Arcidiacono (2004) finds that a person with higher math ability tends to choose certain

[3] The estimated present value of future earnings streams is derived by using panel data, which allows the author to observe the annual earnings of college majors for many years after graduation.

[4] Expected earnings here are a weighted average of earnings when a person successfully graduates in one major and alternative earnings when a person fails to graduate in any other majors.

fields. Following his previous paper, Arcidiacono et al. (2012) employ data collected from Duke University and again show the importance of expected earnings in determining one's major.

While the above papers usually add gender, socioeconomic status, and family background as covariates in regressions, some studies focus on the effect of these variables on the choice of college major. Leppel (2001) finds that students whose fathers are in professional or executive occupations are more likely to choose engineering or science as their fields of study. Moreover, female students from higher socioeconomic status families are less likely to major in business, while the probability of male students choosing business increases. Ma (2009) also finds a similar result and shows that female students from lower socioeconomic status families tend to choose more lucrative majors like business or science while avoiding riskier majors like humanities. Robst (2007a) points out that choosing a career path unrelated to one's field of study is costly.That study shows that 55% of individuals report that their job and field of study are closely related, and 25% of people report that they are somewhat related. Hence, most people choose jobs at least somewhat related to their majors.

Aside from the empirical studies noted above, Altonji (1993) constructs a sequential model that emphasizes the importance of uncertainty and analyzes returns to post-secondary education across different fields of study. Zafar (2013) uses the same sequential model, but focuses more on the role of genders in major choice. Altonji et al. (2012) present a dynamic model that considers both education and occupation choices. The model not only provides a theoretical basis for the choice of college education and major, but also offers an insight of how labor market outcomes can influence people's decisions as students. The paper also provides a comprehensive survey of empirical studies on the demand and returns to education in different phases and shows the recent trends in college majors by using ACS data.

Due to the growing influence of China in international trade over the last 20 years and the continuously decreasing share of the manufacturing sector in U.S. GDP, several papers attempt to show that import competition from manufacturers in China does have significant effects on either employment or wages of U.S. manufacturing industries. For example, Autor, Dorn, and G. Hanson

(2013) analyze the influence of import competition from China on U.S. local labor markets, and find that the rising import competition between 1990 and 2007 leads to reduced employment in the U.S. manufacturing sector.[5] Even after restricting manufacturing employees to those with a college education, the import shocks from China still negatively affect employment. Similarly, Acemoglu et al. (2016) also attribute the huge contraction in manufacturing employment between 2000 and 2007 to increasingly growing competition from China. Their results show that employment of both production (low-skilled) and non-production (high-skilled) workers is seriously affected. The magnitude of these negative effects is even larger after considering sectoral linages by using input-output tables. Usually, no significant negative effects on wages are found in the U.S. manufacturing sector if we measure import competition at the industry level, but if the impact is measured at the occupational level, the negative effects become relatively significant (Ebenstein et al. 2011).

Greenland and Lopresti (2016) exploit the shock from Chinese imports and make a linkage between U.S. high school graduation rates and the intensity of Chinese import competition on local labor markets. They find that there are nontrivial increases in high school graduation rates at places that are more affected by Chinese import competition.[6] The rationale behind their findings is related to my paper: students guard themselves against lost job opportunities due to Chinese import competition by acquiring more education for a higher stream of future income. Weinstein (2019) explores the relationship between local labor demand and college major choice, and finds that universities located in areas exposed to more sectoral demand shocks experience greater changes in the relevant majors. My work combines elements from Greenland and Lopresti (2016) and Weinstein (2019) since I use Chinese import competition and try to see whether the effect of import competition on local labor markets can have any indirect impact on human capital accumulation (major choice).

[5] Local markets refer to commuting zones (CZ). In their paper, they divide mainland states into 722 CZs.

[6] In the appendix, I show that Chinese import competition has a negative effect on the probability of students pursuing college education. Please see subsection A.2.

1.3 Possible Channels

There are two possible channels through which Chinese import competition could affect students' decisions on the choice of college major. The first channel is the expected earnings, or expected future income, of a major. As mentioned in section 1.2, several empirical studies show that expected earnings play a vital role in deciding students' college majors (Berger 1988; Montmarquette et al. 2002; Arcidiacono 2004; Arcidiacono et al. 2012). Aside from empirical studies, structural models also view expected earnings as one of the important labor market outcomes that could influence students' decisions (Altonji 1993; Altonji et al. 2012). While the effect of Chinese import competition on wages at the industry level is not obvious, negative effects can be found at the occupation level (Ebenstein et al. 2011).

The second channel is employment opportunities, or vacancies for a college major on the job market. Most empirical or theoretical studies on major choice do not explicitly include this factor in their models, but Weinstein (2019) exclusively focuses on how a local sectoral shock affects the local demand for certain college majors. Several studies have found the negative effects of Chinese import competition on employment in the U.S. manufacturing sector (Autor, Dorn, and G. Hanson 2013; Acemoglu et al. 2016). Accordingly, I view employment as another channel.

1.4 Data

I use the Public Use Microdata Sample (PUMS) from the American Community Survey (ACS). PUMS collects data on approximately 1% of the United States population every year. It provides information on people's demographics, education, and career background. Moreover, PUMS started to have people report their college majors if respondents had at least a bachelor's degree at the time of the survey since 2009. The survey also asks people to report the industries in which they work (NAICS industry codes). However, one drawback of PUMS is that it provides little information that is crucial in deciding people's choices of college major such as parents' educational levels or respondents' previous academic performance.[7] In this paper, I only choose people who possessed

[7]This problem is also pointed out in Orrenius and Zavodny (2015).

a bachelor's degree and were aged 23-25 at the time of PUMS 2009-2017 to exploit the growing exposure to imports from China. The reason I restrict my sample to those aged 23-25 is that these people were attending high school in the 2000s, which happens to be the period of China experiencing its accelerated export growth.

Table 1.1: Summary Statistics.

	All	Males	Females
% of bachelor's degree or above:			
2009	28.96	23.66	34.18
2017	31.14	25.98	36.56
2009-2017	29.29	24.19	34.56
% of engineering majors			
2009	5.84	11.33	2.09
2017	7.6	13.97	2.84
2009-2017	6.4	12.17	2.23

Note: The numbers in this table are calculated by using people aged 23-25 from PUMS 2009-2017.

Table 1.1 shows the summary statistics of PUMS 2009-2017. From the table, we observe an increasing percentage of people getting bachelor's degrees or above during the sample period. The percentage of females with a bachelor's degree or above is higher than males' by 10 percentage points. The percentage of people choosing engineering majors is increasing for both males and females. However, males are still more likely to major in engineering fields than females.

Fig. 1.4 shows the proportions of engineering degrees in each state between the years of 2009 and 2017. The figure is drawn by using PUMS 2009 and 2017 based on respondents' state of birth.[8] States located above the 45 degree line suggest an increase in the proportion of engineering degrees while the ones located below the diagonal line indicate a decrease in the proportion. We observe that only 13 states are below the line, two states are on the line, and the remaining 35 states plus Washington, D.C. are above the line.[9]

Aside from the nine rounds of PUMS, I also use other data sources to construct the covariates

[8] I also restrict the respondents to people aged 23-25.

[9] In the appendix, I also draw a similar plot for the six selected engineering majors. Please see Fig. A.3 The process of choosing the six majors is explained in detail in section 1.5.

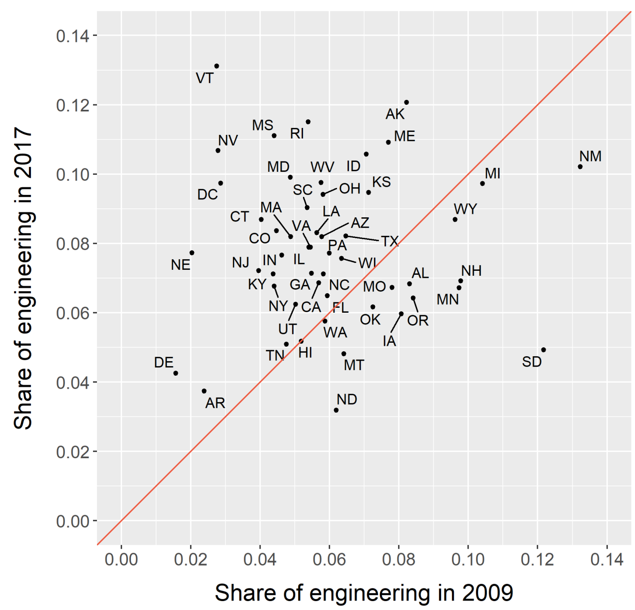

Figure 1.1: Proportions of Engineering Degrees by State between PUMS 2009 and 2017 Based on Respondents' State of Birth.

in my model. The share of population that has a degree less than high school and the share of population aged 16-17 that is foreign-born are derived by using the data from Integrated Public Use Microdata Series (IPUMS). Net migration in each state is created by using the dataset of the National Bureau of Economic Research, which provides annual county-level population data by age, race, and sex since 1990.

For my measure of import comeptition from China, I use two data sources. First, I use U.S. import data from Schott (2008). Second, I use trade data from the United Nations Comtrade Database (UN comtrade) to construct my instrumental variables. For the employment data in each state, I use the County Business Patterns (CBP) dataset, which contains detailed county-level NAICS employment information. Moreover, I obtain the share of enrollment of non-resident aliens, the number of graduates in computer science and engineering fields, and the number of 4-year degree granting institutions in each state from the dataset of the National Center for Education Statistics (NCES).

Fig. 1.2 shows the overall trend of engineering degrees in the U.S. from 1991 through 2017.

The figure is drawn by using data from NCES. The red solid line suggests a downward sloping trend starting from 1991 till 2009. The share of engineering degrees drops from 7.2% to 5.2% in that period. After 2009, the proportion climbs up and reaches 6.8% in 2017. Since different genders might show differential trends over time, I draw dashed and dot-dash lines for males and females, respectively. The proportion of engineering degrees for males suggests a similar trend before 2009. The share drops from 13.6% to 10.3% in the period. For females we cannot observe such a trend. However, the proportions for males and females both climb up after 2009.[10]

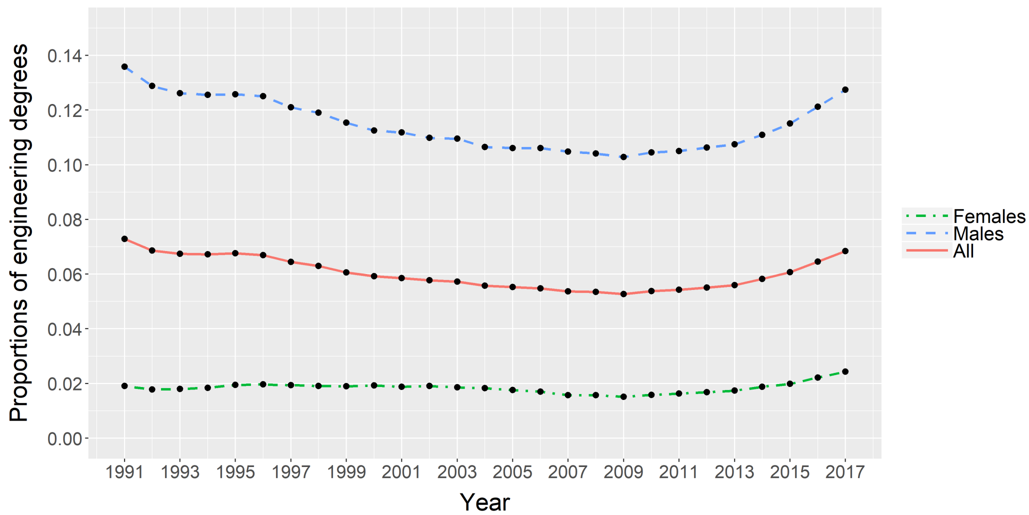

Figure 1.2: Proportions of Engineering Degrees in the United States from 1991 through 2017.

1.5 Empirical Approach

1.5.1 College Majors of Interest

In order to analyze the effect of import competition from China on American students' choice of college major, I need to select college majors that are likely to be affected by the growing competition from China. The possible choices would be majors that are closely related to the S&E fields, since graduates in S&E majors compared to other fields are more likely to work in the

[10]In the appendix, I also draw a similar plot for the six selected engineering majors by using PUMS 2009 through 2017. Please see Fig. A.4.

manufacturing sector, which has been seriously affected by intense competition from China in the past two decades. In this paper, I focus primarily on engineering majors.

There are two criteria I apply to choosing the college majors. First, at least 15% of college graduates aged 23-25 in engineering fields work in manufacturing industries in each round of the survey. Second, following the first criterion the proportion should be relatively stable across the nine rounds of PUMS. In fear of underestimating the proportions, I also calculate the proportions by using people aged 30-33.[11] There are six engineering majors selected for my research: general, chemical, electrical, industrial and manufacturing, mechanical, and miscellaneous engineering. The following Fig. 1.3 shows the proportions of the six engineering majors in the manufacturing sector.[12] The vertical axis represents the proportion, and the horizontal axis is the survey year. The solid line in each graph represents the proportion by using people aged 23-25, while the dashed line shows the proportion by using people aged 30-33. Fig. 1.3 suggests that the proportion of miscellaneous engineering is not as stable and large as the other five majors. However, I still include it since the proportion becomes larger and more stable when it is calculated by using people aged 30-33.[13])

The stability of the proportion is crucial since it would give students an impression that a stable portion of graduates in one of these fields tends to work in the manufacturing sector and the performance of the manufacturing sector will affect their expectations of future earnings and job availability, which are important determinants of college majors. Therefore, when a college student considers which major to choose, the performances of manufacturing industries should enter a student's decision-making process. The decreasing job opportunities of some manufacturing industries due to increasing competition from China negatively affect students' expectations, which would further lower their probability of choosing these engineering majors. On the other hand, if

[11] People who are aged 30-33 in each round of PUMS were around 23-25 years old when the respondents in my sample attended high school. Thus, I also calculate the proportions by using people aged 30-33 to observe their shares in the manufacturing sector. However, one concern is that the proportions of either age range might be biased. Since the first round of the dataset is PUMS 2009, this implies these shares are all after instead of before intense Chinese import shock.

[12] There are 27 engineering majors defined by PUMS. Fig. A.1 in the appendix shows the proportions of the remaining 21 engineering majors.

[13] Fig. A.2 in the appendix shows the proportions of the six majors in the selected manufacturing industries.

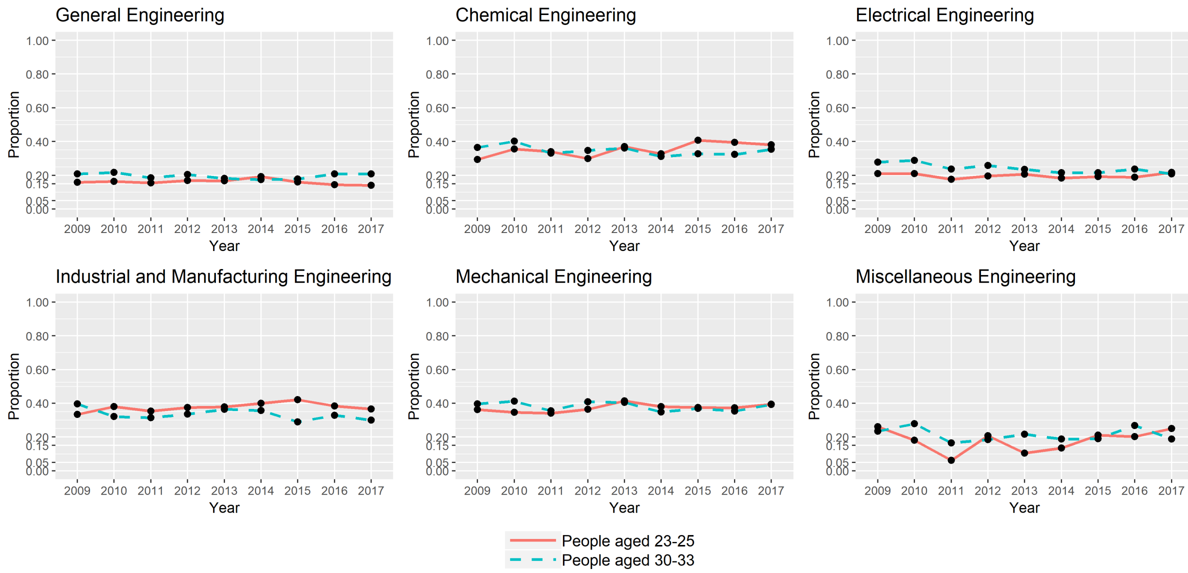

Figure 1.3: Proportions of the Six Engineering Majors in the Manufacturing Sector.

a college major shows a relatively unstable or low proportion of its graduates in the manufacturing sector, then this would imply that college graduates in this field can easily find a job in a non-manufacturing sector and thus are not subject to the negative effects of Chinese import competition. Accordingly, college students will not view increasing competition from China as the downside of choosing this major. The decision-making process is much less affected by Chinese import competition when students expect the connection between a college major and its corresponding manufacturing industries is weak.

1.5.2 Selected Manufacturing Industries

Once the majors of interest are decided, the next question is which manufacturing industries should be considered here. Each round of PUMS provides information about the industry in which people currently work.[14] There are two criteria that help to select the corresponding industries of the six engineering majors. First, at least three out of the six selected majors work in the industry, and then the industry will be selected in that round of PUMS. Second, the industry should be selected 8 times out of 9 rounds of PUMS. These two criteria are intended to ensure the selected industries

[14]PUMS provides NAICS industry codes, and most of them are at the 4-digit level.

have a strong connection with my choice of the six engineering majors across years.[15] According to these two criteria, 13 ACS-defined manufacturing industries are selected. The following table lists the industries, the descriptions, and their corresponding nineteen 4-digit NAICS codes. In the appendix, Fig. A.5 shows that the selected industries account for 40% of the output of the U.S. manufacturing sector in the 2000s.

Table 1.2: Selected NAICS Industries.

ACS-defined codes	NAICS codes	Description in ACS
336M[a]	3361,3362,3363	Motor vehicles and motor vehicle equipment
3254	3254	Pharmaceuticals and medicines
3366	3366	Ship and boat building
3391	3391	Medical equipment and supplies
32411	3241	Petroleum refining
325M	3251,3259	Industrial and miscellaneous chemicals
331M	3311,3312	Iron and steel mills and steel products
3331M	3331	Construction, and mining and oil and gas field machinery
334M2	3344,3346	Electronic components and products, n.e.c.
335M	3351,3353,3359	Electric lighting, and electrical equipment. Manufacturing, and other electrical components.
33641M1	3364	Aircraft and parts
33641M2	3364	Aerospace products and parts
3399ZM[b]	3399	Miscellaneous manufacturing, n.e.c.

a. M=Multiple NAICS codes.
b. Z=Part of the NAICS industry, but has a unique Census code.
c. n.e.c=not elsewhere classified.

1.5.3 Econometric Specifications

$$\begin{aligned}\text{Engineering}_{i,s,t} &= \alpha + \beta \text{IMP}_{s,t-2} + \overline{\text{State}}_{s,t}\delta + \text{Individual}_{i,s}\rho \\ &\quad + \phi_s + \eta_w + \varphi_t + \varepsilon_{i,s,t}, \text{ where}\end{aligned} \tag{1.1}$$

$$\text{IMP}_{s,t-2} = \sum_{j \in J} \frac{L_{s,j,t-2}}{L_{j,t-2}} \frac{import^{CHN}_{j,t-2}}{L_{s,t-2}}. \tag{1.2}$$

[15]For example, if I can only observe graduates in chemical engineering in the medical equipment industry in PUMS 2009 and do not observe the other five majors in the industry in the same round of survey, then the medical equipment industry will not be chosen for PUMS 2009.

Equation 1.1 shows the main regression model in this paper. First, I use the linear probability model to analyze the relationship between import competition from China and the probability of college students choosing one of the six engineering majors. The dependent variable, $\text{Engineering}_{i,s,t}$, is equal to 1 if individual i who was born in state s chose one of the six engineering majors in year t and equal to 0 otherwise. Here, I assume individuals decide or at least form a belief of which college major they would like to choose at the age of 18. Thus, t is the year when respondents are 18 years old. $\text{IMP}_{s,t-2}$ is a measure of weighted import competition from China in state s in year $t-2$ as shown in equation 1.2, from which I refer to Autor, Dorn, and G. Hanson (2013). $import^{CHN}_{j,t-2}$ represents U.S. imports of industry j from China in year $t-2$. Since it takes time for the U.S. labor market to react to Chinese import competition and for students' expectations to change, I use a two-year lagged measure. However, the main difference between my measure and theirs is that I use the level of imports in each year instead of the changes of imports across two periods. The varying value of the fraction, $L_{s,j,t-2}/L_{j,t-2}$, is the main reason why industry j faces differential exposure to competition from China across states. Furthermore, $L_{s,j,t-2}$ is the employment of industry j in state s, and $L_{j,t-2}$ stands for the total employment of industry j in the U.S. The larger the fraction is, the more intense foreign competition industry j faces in that state. For instance, workers in Michigan make up a non-trivial portion of the U.S. auto industry, and thus Michigan plays an important role in the industry, and so we should expect to see the value of $L_{MI,auto,t-2}/L_{auto,t-2}$ be relatively larger than in other states. $L_{s,t-2}$ is the employment in state s in year $t-2$. J is the set of industries I choose.

$\overline{\text{State}}_{s,t}$ includes several state-level variables to control for any potential bias that could result from the failure to include respondents' family background and personal migration information.[16] These variables include the net population flow of people aged 15-19 by state, the share of the population aged 45-60 that has a degree less than high school by state and race, the share of the population aged 45-60 receiving welfare benefits from the government by state and race, and three proxies for socioeconomic status, occupational status, and occupational earnings level by state and

[16] I use the average values from year $t-2$ through t to construct the state-level controls.

race.[17] Individual$_{i,s}$ includes individual characteristics that are constant across years such as race and gender.[18] The state-of-birth fixed effect, ϕ_s, is included in the regression to control for any unobservables that do not change over time in each state such as geographical properties or cultural factors that are specific to each state. For the robustness of my results, the state-of-work fixed effect, η_w, is added to the regression to control for time-invariant unobservables in future workplaces. For example, students' prior perception of job markets and working conditions in other states might affect my results. The year fixed effect, φ_t, is also included to control for the aggregate trend in the year when the students were 18 years old. For example, the nationwide performance of industries or policies on education across the country may have non-trivial effects on students' decision on college majors. $\varepsilon_{i,s,t}$ is the error term. The standard errors are robust to heteroskedasticity and clustered on state of birth to allow any serial correlation within states.

An assumption behind the measure in equation 1.2 is that people who were born in state s still stay in the same state while attending high school. This is a very strong assumption that is not likely to hold, since it is highly possible for people to live in a state different from their state of birth due to parents' career changes. Unfortunately, PUMS does not provide information on migration history, and biased estimates of the effect of import competition would be obtained if the measure does not account for the possibility of people migrating to other states. Therefore, a new measure that accounts for the possibility of migration is introduced in equation 1.3, where the baseline measure in equation 1.2 is weighted by the probability of people born in state s, but who lived in state b. $\tau_{s,b,t-2}$, the proxy for this probability, is the percentage of people who were 16-18 years old and born in state s, but who lived in state b in year $t-2$.[19] $B_{s,t-2}$ is the set of states where people aged 16-18 and born in state s lived in year $t-2$. $s \in B_{s,t-2}$ means the state of birth is always included in the set.

[17]The proxies are the Hauser-Warren socioeconomic index, Nam-Powers-Boyd occupational status score, and occupational earnings score, which are all constructed by PUMS.

[18]I classify the races into five categories: Whites, Blacks, American Indians/Alaska natives, Asians, and people with multiple races.

[19]One example is if an individual was 18 years old in the year of 2002 (t is 2002). PUMS 2000 would be used to calculate the percentage.

$$\widehat{\text{IMP}}_{s,t-2} = \sum_{b \in B_{s,t-2}} \sum_{j \in J} \tau_{s,b,t-2} * \frac{L_{b,j,t-2}}{L_{j,t-2}} \frac{import^{CHN}_{j,t-2}}{L_{b,t-2}}, \text{ and } s \in B_{s,t-2}. \tag{1.3}$$

Even though the measure in equation 1.3 accounts for migration, it does not take into account import competition from neighboring states. Without considering the potential spillovers from neighboring states, the measure may not completely reflect students' perception of import competition from China due to the possibility of working in other states after graduation. For example, at least 40% of Michigan State University's alumni choose to work in other states, and the number is even larger for the University of Michigan.[20] Therefore, a measure that further accounts for students' prior expectations of working in other states can better gauge the influence of trade exposure on their choice of college major.

Equation 1.4 shows the new measure of foreign competition, $\widetilde{\text{IMP}}_{s,t-2}$, which is weighted by the probability of working in other states. $\psi_{s,w,t-2}$, the proxy for this probability, is the percentage of people who were aged 23-25, born in state s, and at least possessed a college degree, but worked in state w in year $t-2$. $W_{s,t-2}$ is a collection of states of work, including all the states where the targeted people born in state s and worked in year $t-2$. $s \in W_{s,t-2}$ means the state of birth is always included in the collection of states of work. Next, the RHS of equation 1.4 can be decomposed into two terms as shown in equation 1.5. The first term captures import competition from China faced by states of birth, while the second term captures Chinese import competition faced by states of work due to the possibilities of working in other states. By writing the measure of import competition in this way, I can compare the relative influence of Chinese import competition in states of birth to the counterpart in states of work on students' choice of college major.

[20] The number is from an interesting article in the Wall Street Journal titled "Where Graduates Move After College", which shows the movement of alumni from 445 U.S. universities and colleges. For more information, please visit `https://www.wsj.com/graphics/where-graduates-move-after-college/`.

$$\widetilde{\text{IMP}}_{s,t-2} = \sum_{w \in W_{s,t-2}} \psi_{s,w,t-2} * \widehat{\text{IMP}}_{w,t-2}, \text{ and } s \in W_{s,t-2} \tag{1.4}$$

$$= \underbrace{\psi_{s,s,t-2} * \widehat{\text{IMP}}_{s,t-2}}_{\text{state of birth}} + \underbrace{\sum_{w \neq s, w \in W_{s,t-2}} \psi_{s,w,t-2} * \widehat{\text{IMP}}_{w,t-2}}_{\text{state of work}}. \tag{1.5}$$

1.5.4 Baseline Estimates

Table 1.3: Ordinary Least Squares Results.

	(1)	(2)	(3)	(4)	(5)
(Imports from China to US)/worker (IMP)	-0.0158^{***} (−2.70)	-0.0156^{**} (−2.45)			
IMP weighted by migration			-0.0186^{**} (−2.51)		
IMP weighted by migration and workplace				-0.0255^{***} (−2.50)	
IMP weighted by migration and workplace (state of birth)					-0.0260^{**} (−2.56)
IMP weighted by migration and workplace (other states)					−0.0083 (−0.44)
State-level controls	No	Yes	Yes	Yes	Yes
Number of observations	182,461	182,461	182,461	182,461	182,461
R^2	0.0303	0.0303	0.0303	0.0303	0.0303

Notes: State-level controls include the net population flow of people aged 15-19 by state, the share of the population aged 45-60 with a high school degree or below by state and race, the share of the population aged 45-60 receiving welfare benefits from the government by state and race, and three proxies for socioeconomic status, occupational status level, and earnings by state and race. All imports data are in 2007 US$ and values are in thousands. Standard errors are robust to heteroskedasticity and clustered on state of birth. t-statistics are in parentheses. State of birth, state of work, and year fixed effects are included in each column. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 1.3 shows the OLS results by using different measures of Chinese import competition. While both columns 1 and 2 use the same measure in equation 1.2, several state-level controls are introduced in column 2 to prevent potential bias that will contaminate the results. For example, the negative population flow of people aged 15-19 might be a sign of parents' job changes due to increased Chinese import competition. Not including the net population flow might lead to underestimating the effects of Chinese trade exposure on people's choice of college major. Moreover, parents' educational level plays a vital role in determining children's majors in college according to the previous literature (Leppel 2001). To control for the potential influence from parents' education, I also include the percentage of the population aged 45-60 with a high school degree or below by state and race. Female students from a lower socioeconomic family tend to choose a major that will provide them with more stable job opportunities (Ma 2009). Accordingly, I include the share of the population aged 45-60 receiving welfare benefits from the government and three proxies for socioeconomic status to control for the effects of family background on people's choice of majors. However, column 2 shows that the estimated coefficient on IMP almost remains the same after adding the state-level controls. From the trade data, Chinese imports per worker increase by \$528, \$528, and \$496 between 2000-2010 for the measures in equations 1.2, 1.3, and 1.4, respectively. Following the same method in Autor, Dorn, and G. Hanson 2013 I only elicit the supply driven part of Chinese imports to avoid overestimating the negative effects of Chinese imports on students' major choice.[21] Thus, the imports become \$253, \$253, and \$238 for each measure after adjustment.

Since the increase in Chinese import per worker is \$253 for the baseline measure during the period of 2000-2010, the estimated coefficient in column 2 is associated with a 0.39 percentage point, or equivalently 9.15%, decrease in the probability of choosing the six engineering majors.[22] In column 3, the specification uses the measure of Chinese import competition weighted by the probability of moving to other states. The estimated effect of Chinese import competition on choice of college major becomes larger if the measure accounts for the possibility of people not staying in their states of birth. The increase in Chinese import per worker weighted by migration is \$253, which is associated with a 0.47 percentage point, or equivalently 10.83%, decrease in the probability of majoring in one of the six engineering fields.[23] Next, the specification in column 4 uses the measure weighted by both migration and workplace, and the estimated coefficient in

[21] The original increases in Chinese imports per worker are \$528, \$528, and \$496 between 2000-2010 for the measures in equations 1.2, 1.3, and 1.4, respectively. To elicit the supply driven part of the imports I multiply each original import by 0.48. Please refer to the appendix of Autor, Dorn, and G. Hanson 2013 for details.

[22] According to PUMS, the share of people aged 23-25 owning a degree in one of the six engineering majors is 3.87% between 2000 and 2010. Thus, $0.39\%/(0.39\% + 3.87\%) \approx 9.15\%$.

[23] $0.47\%/(0.47\% + 3.87\%) \approx 10.83\%$.

absolute value further increases to 0.0255, which is 37% higher than the one in column 3. The associated effect is a 0.61 percentage point, or equivalently 13.62%, decrease in the probability by using the increase in Chinese import per worker weighted by migration and workplace, \$238, in the 2000s.[24] In column 5, the last specification uses the measure that differentiates the sources of Chinese import competition: state of birth and other states. Even though both estimated coefficients on IMP are negative, the effect from other states is not statistically significant even at the 10% level, while the effect from state of birth remains strong and significant at the 5% level.

1.5.5 Instrumental Variables

A concern for my identification strategy is the existence of endogeneity in my specification. To have a better idea of the sources of endogeneity, the error term in equation 1.1 is decomposed into three parts as shown in equation 1.6 below. The first two terms on the RHS of equation 1.6 are the two sources of endogeneity, and the last term is the idiosyncratic error.

$$\varepsilon_{i,s,t} = \Gamma_{i,s,t} Z + \theta_{s,t-2} + \mu_{i,s,t} \tag{1.6}$$

The vector, $\Gamma_{i,s,t}$, contains individual controls that are important in determining students' choice of college major, but are lacking in PUMS such as parents' educational levels, socioeconomic status, personal migration history, previous academic performance, etc. Z is a vector of coefficients corresponding to $\Gamma_{i,s,t}$. Failing to include these control variables in the regression will lead to serious omitted variable bias in the estimates of the effect of Chinese import competition on the choice of college major. The second source of endogeneity, $\theta_{s,t-2}$, results from the failure to control for the U.S. demand for imports from China. As pointed out in Autor, Dorn, and G. Hanson (2013), only when this demand is controlled can the unbiased effect of Chinese imports on the U.S. labor market be captured. To address the two sources of endogeneity, I follow Autor, Dorn, and G. Hanson (2013) and build a similar instrument.

[24] $0.61\%/(0.61\% + 3.87\%) \approx 13.62\%$.

$$\text{IMP}^{Other}_{s,t-2} = \sum_{j \in J} \frac{L_{s,j,t-7}}{L_{j,t-7}} \frac{import^{Other}_{j,t-2}}{L_{s,t-7}}. \tag{1.7}$$

Equation 1.7 shows the instrument for the measure of Chinese competition in equation 1.2. $\text{import}^{Other}_{s,t-2}$ is total imports of eight other high-income countries from China.[25] For fear of underestimating the impact of Chinese import competition due to people's prior expectations of and reaction to increasing Chinese imports, I use seven-year-lagged employment variables (five-year-lagged compared to $\text{IMP}_{s,t-2}$) to avoid the underestimation problem. The instrument is meant to address the second source of endogeneity in Autor, Dorn, and G. Hanson (2013). As for the first source of endogeneity, the instrument is intuitively not correlated with personal academic performance and parents' educational levels. However, the potential correlation between the instrument and other personal properties like parents' occupations or migration history still causes concern over the validity of the instrument. For example, the growing imports from China might significantly influence the employment structure of the United States, which may affect the working age population's career paths. The changes in parents' career paths could then influence children's migration history. In this case, the exogeneity restriction of the instrument may not hold. To address the concern, I include a group of state-level controls that relate to migration and family background such as net population flow, the share of the population aged 45-60 with a high school degree or below, the share of the population aged 45-60 receiving welfare benefits from the government, and proxies for socioeconomic status as noted above. In case of violation of exogeneity restriction, I also use the gravity model to obtain the predicted imports of the selected industries and treat them as my new instruments for further robustness check. Appendix A.1 gives more details about the gravity equations. Table A.1 in the appendix reports the 2SLS results by using the new instruments.

$$\widehat{\text{IMP}}^{Other}_{s,t-2} = \sum_{b \in B_{s,t-7}} \sum_{j \in J} \tau_{b,t-7} * \frac{L_{b,j,t-7}}{L_{j,t-7}} \frac{import^{Other}_{j,t-2}}{L_{b,t-7}}, \text{ and } s \in B_{s,t-7}. \tag{1.8}$$

[25]The eight countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

$$\widetilde{\text{IMP}}_{s,t-2}^{Other} = \sum_{w \in W_{s,t-7}} \psi_{s,w,t-7} * \widehat{\text{IMP}}_{w,t-2}^{Other}, \text{ and } s \in W_{s,t-7} \tag{1.9}$$

$$= \psi_{s,s,t-7} * \widehat{\text{IMP}}_{s,t-2}^{Other} + \sum_{w \neq s, w \in W_{s,t-7}} \psi_{s,w,t-7} * \widehat{\text{IMP}}_{w,t-2}^{Other}. \tag{1.10}$$

Equations 1.8, 1.9, and 1.10 are the instruments for the measures in equations 1.3, 1.4, and 1.5, respectively. To prevent the underestimation problem mentioned above, in addition to using seven-year-lagged employment variables I also use the seven-year-lagged values for the probabilities of migrating to and working in other states $\tau_{b,t-7}$ and $\psi_{s,w,t-7}$.[26]

1.6 Results

1.6.1 Probabilities of Choosing the Six Engineering Majors

The estimated effects of Chinese trade exposure on choice of college major could be biased if U.S. demand for Chinese imports is not considered or important variables are omitted in the specifications. Therefore, I use the instrumental variables to address the two sources of endogeneity, and Table 1.4 reports the two-stage least squares results. Panel A of Table 1.4 shows the estimated coefficients of different measures of Chinese import competition, and panel B displays the first stage of 2SLS. As shown in panel B, none of the instruments used in this paper show a sign of being weak since their F statistics are way above 10, which is a criterion proposed by Stock and Yogo (2005). Column 1 shows the estimated coefficient on IMP is −0.0183, which is slightly larger than its counterpart in column 2 of Table 1.3. In column 2, the estimated coefficient on IMP weighted by migration is qualitatively the same as the result in the OLS specification, but remains significant at the 5% level. The associated effect now is a 0.49 percentage point decrease in the probability of choosing the six engineering majors. However, the estimated coefficients in columns 3 and 4 suggest smaller effects of Chinese import competition on students' choice of college major once the endogeneity is addressed by using the instruments. An estimated coefficient of −0.0227 in column

[26] Due to data limitations of PUMS before 2000, if $t-7$ is smaller than 2000, then the two proxies, τ and ψ, are calculated by using PUMS 1990 instead.

Table 1.4: Estimates of Two-Stage Least Squares.

	A. 2SLS results			
	(1)	(2)	(3)	(4)
(Imports from China to U.S.)/worker (IMP)	−0.0183** (−2.24)			
IMP weighted by migration		−0.0193** (−2.19)		
IMP weighted by migration and workplace			−0.0227* (−1.80)	
IMP weighted by migration and workplace (state of birth)				−0.0240* (−1.95)
IMP weighted by migration and workplace (other states)				−0.0085 (−0.39)
State-level controls	Yes	Yes	Yes	Yes
R^2	0.0303	0.0303	0.0303	0.0303
	B. First Stage of 2SLS estimates			
(Imports from China to Other)/worker (IMP^{other})	0.5917*** (8.10)			
IMP^{other} weighted by migration		0.6339*** (10.50)		
IMP^{other} weighted by migration and workplace			0.7180*** (12.23)	
F-Stat	65.58	109.29	149.54	

Notes: Standard errors are robust to heteroskedasticity and clustered on state of birth. t-statistics are in parentheses. State of birth, state of work, and year fixed effects are included in each column. The number of observations is 182,461. All imports data are in 2007 US$ and values are in thousands. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

3 implies a 0.54 percentage point decrease in the probability of choosing the six majors. In column 4, the statistical significance of IMP (state of birth) and the insignificance of IMP (other states) again suggest that Chinese trade exposure in people's state of birth exerts more influence on their choice of major than the influence from other states.

To test the robustness of my results, I include additional state-level controls and fixed effects.[27] For example, foreign-born immigrants could reduce native students' opportunity to study S&E majors (Orrenius and Zavodny 2015). To address the concern, I include the share of people aged 16-18 who were foreign-born by race to account for the competition from immigrants. Another concern is that foreign students can also be a non-trivial source of competition for admission to

[27] The additional state-level controls I include here are also the average values from year $t-2$ through t.

the engineering programs. Thus, I include the percentage of non-resident aliens in fall enrollment as well to account for the crowding-out effect due to the increasing number of foreign students in colleges. Moreover, the number of institutions available and the number of students accepted to engineering majors each year could also bias my results. For instance, if there are less colleges available to students or colleges provide less engineering programs for students to choose, then the estimated negative effects of Chinese imports would also be biased upward. Hence, I include the number of graduates in computer science or engineering and the number of 4-year degree granting private and public facilities to indirectly control for the availability of these majors to students.[28] Lastly, I also include year×race and year×gender fixed effects to consider the relative easiness for different gender and racial groups to study these majors over the period. The two fixed effects can also address the concern that nationwide education policies might favor or encourage people of certain gender or racial groups to choose engineering majors.

Table 1.5 reports the 2SLS results after I include the additional controls and fixed effects mentioned above. Panel A of Table 1.5 shows the estimated coefficients on IMP, and panel B displays the additional controls and fixed effects included in each specification. Due to space limitations, this table only reports the results of two alternative IMP measures: IMP weighted by migration and IMP weighted by migration and workplace. Columns 3 and 6 demonstrate the results when all the additional controls and fixed effects are included in the specifications. In column 3 of panel A, the estimated coefficient on IMP weighted by migration is -0.0246, whose magnitude is greater than the result in column 2 of Table 1.4. The estimated coefficient also implies a 0.62 percentage point, or equivalently 13.81%, decrease in the probability of majoring in one of the six engineering fields.[29] The estimated coefficient on IMP weighted by migration and workplace in column 6 also suggests an increase in the negative effect of Chinese competition on the choice of engineering majors. The estimated coefficient in column 6 is associated with a 0.69 percentage point, or equivalently 15.13%, decrease in the probability of choosing the six majors. The increase

[28] For example, I use the number of graduates in computer science or engineering in 2010 as a proxy for the number of students admitted to computer science or engineering in 2006.

[29] According to PUMS, the share of people aged 23-25 owning a degree in one of the six engineering majors is 3.87% between 2000 and 2010. Then $0.62\%/(0.62\% + 3.87\%) \approx 13.81\%$

Table 1.5: Robustness Check for 2SLS Estimates.

	A. 2SLS results					
	(1)	(2)	(3)	(4)	(5)	(6)
IMP weighted by migration	−0.0202**	−0.0242***	−0.0246***			
	(−2.26)	(−2.68)	(−2.81)			
IMP weighted by migration and workplace				−0.0239*	−0.0283**	−0.0289**
				(−1.81)	(−2.12)	(−2.22)
	B. Additional Controls					
Share of the population: Foreign-born	0.0325	−0.0025	−0.0475	0.03	−0.0047	−0.0509
	(0.56)	(−0.04)	(−0.80)	(0.49)	(−0.08)	(−0.81)
Share of enrollment: Non-resident aliens		0.1068	0.1360		0.0964	0.1264
		(0.67)	(0.86)		(0.62)	(0.82)
Number of graduates (log): CS & Engineering		0.0092	0.0117		0.0082	0.0108
		(1.22)	(1.61)		(1.12)	(1.52)
Number of institutions:						
4-yr degree granting public			0.0008***			0.0008***
			(3.27)			(3.14)
4-yr degree granting private			−0.0003*			−0.0003*
			(−1.82)			(−1.81)
Year×race fixed effects	No	Yes	Yes	No	Yes	Yes
Year×gender fixed effects	No	No	Yes	No	No	Yes
State-level controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0303	0.0306	0.0308	0.0303	0.0306	0.0308

Notes: Standard errors are robust to heteroskedasticity and clustered on state of birth. t-statistics are in parentheses. State of birth, state of work, and year fixed effects are included in each column. The number of observations is 182,461. All imports data are in 2007 US$ and values are in thousands. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

in the magnitudes of the estimated coefficients in both columns 3 and 6 may suggest the existence of omitted variable bias in Table 1.4. Table 1.5 shows that my results hold firmly and remain statistically significant at either the 5% or 1% level after I add controls and fixed effects. As for the additional controls, only the number of 4-year degree granting public institutions suggests a statistically significant and positive effect on the choice of the six engineering majors while the remaining controls are barely statistically significant.

Males are conventionally more likely to choose engineering majors than females, and this phenomenon can also be observed in my data. In my sample, 7.46% of males major in one of the six engineering majors compared to only 1.2% for females. Hence, it is possible that Chinese import competition would have a differential effect on different genders.

Table 1.6 reports the 2SLS results by gender. They suggest that only males are negatively

Table 1.6: 2SLS Estimates by Gender.

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
IMP weighted by migration	-0.0548^{***}			-0.0026		
	(-3.11)			(-0.30)		
IMP weighted by migration and workplace		-0.0663^{***}			-0.0009	
		(-2.76)			(-0.08)	
IMP weighted by migration and workplace (state of birth)			-0.0669^{***}			-0.0014
			(-2.78)			(-0.12)
IMP weighted by migration and workplace (other states)			-0.0565			0.0059
			(-1.42)			(0.33)
Year×race fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	77,602	77,602	77,602	104,859	104,859	104,859

Notes: Standard errors are robust to heteroskedasticity and clustered on state of birth. t-statistics are in parentheses. State of birth, state of work, and year fixed effects are included in each column. State-level and additional controls are also included in each column. All imports data are in 2007 US$ and values are in thousands. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

affected by Chinese import competition, while females do not show any sign of being affected by Chinese trade exposure. The magnitudes of the estimated coefficients in columns 4-6 are relatively small and not statistically significant at the 10% level. For the male sample, columns 1-3 suggest that the estimated coefficients are much larger in each specification compared to the pooled sample case in Table 1.5. In column 1, the estimated coefficient of -0.0548 implies an associated 1.39 percentage point decrease in the probability of choosing the six engineering fields. However, in the pooled sample case the number is only 0.62 percentage points as noted above. The 1.39 percentage points also imply the probability of male students choosing the six engineering majors in the 2000s decreases by 15.71%.[30] In column 2, the estimated coefficient on IMP weighted by migration and workplace is associated with a 1.58 percentage point decrease in probability. This implies the probability of male students choosing the six engineering majors in the 2000s decreases by 17.48%.[31]

Another concern is whether or not the two-year lagged measures of Chinese import competition can appropriately capture the effects of Chinese imports on choice of college major. It is possible

[30] $1.39\%/(1.39\% + 7.46\%) \approx 15.71\%$.

[31] $1.58\%/(1.58\% + 7.46\%) \approx 17.48\%$.

that it takes longer than two years for the influence of Chinese imports to reach students' decision process. For a robustness check, Table 1.7 reports the results when I use the average of two-year and three-year lagged measures of Chinese imports in each specification. The results show that only the estimated coefficients in columns 1 and 2 are statistically significant at the 10% level. The results in columns 3-4 are not statistically significant even though the estimated coefficients are negative. The results in Table 1.7 suggest that the two-year lagged measure exerts the strongest effect on students' choice of college major.

Table 1.7: 2SLS Estimates with Average Lagged Measures of Imports.

	(1)	(2)	(3)	(4)
IMP	−0.0165*			
	(−1.88)			
IMP weighted by		−0.0165*		
migration		(−1.70)		
IMP weighted by			−0.0192	
migration and workplace			(−1.45)	
IMP weighted by				−0.0194
migration and workplace				(−1.47)
(state of birth)				
IMP weighted by				−0.0148
migration and workplace				(−0.54)
(other states)				
Number of observations	182,461	182,461	182,461	182,461

Notes: Standard errors are robust to heteroskedasticity and clustered on the state of birth. t-statistics are in parentheses. State of birth, state of work, and year fixed effects are included in each column. State-level and additional controls are also included in each column. All imports data are in 2007 US$ and values are in thousands. All measures of import competition in this table are the averages of 2yr and 3yr-lagged measures. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Instead of only focusing on the six engineering majors, the effect of Chinese trade exposure on the remaining engineering majors could also provide us with an insight into the trend of college major choice in the 2000s. Students may choose less affected engineering fields to guard themselves against dwindling employment in the U.S. manufacturing sector due to Chinese import competition. I employ similar specifications as stated in Section 1.5.3, but the dependent variable now becomes the less affected engineering majors (i.e. the remaining 21 engineering majors).

Columns 1-3 of Table 1.8 show the results when the dependent variable considers all engineering majors, while columns 4-6 report the results when the dependent variable only uses the less affected engineering majors. Since the measure of import competition in this paper is constructed by using the 19 NAICS manufacturing industries that have a high connection with the six engineering majors, the insignificant results are expected. Contrary to the insignificant results of columns 1-3, the specifications in columns 4-6 suggest Chinese imports have a significant positive effect on the probability of students choosing the less affected engineering majors. This could imply that students do in fact guard themselves against shrinking job opportunities of the selected industries by choosing or switching to engineering majors that provide a job market less impacted by Chinese import competition.

Table 1.8: Effects on the Overall and Less Affected Engineering Majors.

	Dependent variable					
	All engineering majors			Less affected engineering majors		
	(1)	(2)	(3)	(4)	(5)	(6)
Imports from China to US)/worker (IMP)	−0.0091 (−0.85)			0.0132^{*} (1.80)		
IMP weighted by migration		−0.0093 (−0.84)			0.0142^{*} (1.82)	
IMP weighted by migration and workplace (state of birth)			−0.0083 (−0.58)			0.0205^{**} (2.14)
IMP weighted by migration and workplace (other states)			0.0082 (0.28)			0.0257 (1.42)

Notes: Standard errors are robust to heteroskedasticity and clustered on state of birth. t-statistics are in parentheses. State of birth, state of work, and year fixed effects are included in each column. State-level and additional controls are also included in each column. All imports data are in 2007 US$ and values are in thousands. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

Table 1.9 shows the results of the falsification test. The results obtained so far could come from some unobserved long-term factors that drive both students' college major choices and the measures of Chinese import competition. If such factors exist and drive my results, then the measures of trade exposure to Chinese imports should also have significant negative effects on the choice of college major of the older individuals in PUMS (33-35 years old). Thus, I regress the measures of import competition on the major choice of older individuals to see if there are any significant results. Columns 1-3 use the six selected engineering majors as the dependent variable, while columns

4-6 use the less affected engineering majors. According to the table, the estimated coefficients of different specifications show no trace of significant results. Thus, the results I obtained cannot be driven by some long-term trends or unobserved factors.

Table 1.9: Falsification Test.

	People aged 33-35 years old in PUMS					
	The six engineering majors			Less affected engineering majors		
	(1)	(2)	(3)	(4)	(5)	(6)
Imports from China to US)/worker (IMP)	−0.0026 (−0.34)			−0.0068 (−0.96)		
IMP weighted by migration		−0.0039 (−0.44)			−0.0059 (−0.73)	
IMP weighted by migration and workplace			−0.0046 (−0.34)			−0.0038 (−0.33)

Notes: Standard errors are robust to heteroskedasticity and clustered on state of birth. t-statistics are in parentheses. State of birth, state of work, and year fixed effects are included in each column. State-level and additional controls are also included in each column. The number of observations is 152,789. All imports data are in 2007 US$ and values are in thousands. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

1.6.2 Percentages of Choosing Engineering Majors

Even though the results so far have shown that import competition of certain industries from China does lead to a decrease in the probability of students choosing some engineering majors, the results are quite restricted since the implications of these results do not apply to the whole engineering field. To further explore Chinese imports' effects on the whole engineering field, instead of using individual-level data and working on the binary choice model, I use the same sample as above, construct the percentage of choosing engineering fields in each state over the same time period, and treat the percentages as my new dependent variables. By doing so, a balanced state-level panel dataset is obtained.[32] Equation 1.11 below is the new regression model to handle the state-level panel data.

[32] The sample I use consists of three age cohorts (23-25) in each round of PUMS, and these age cohorts correspond to 11 distinct years.

$$\text{Percentage}_{s,t} = \alpha + \beta \text{IMP}_{s,t-2} + \overline{\text{State}}_{s,t}\delta + \phi_{s,t} + \varepsilon_{s,t} \quad (1.11)$$

$\text{Percentage}_{s,t}$ is the percentage of people who were born in state s and chose an engineering field as their major in year t. Here, I also assume t is the year when people are 18 years old and determine their college majors. $\text{IMP}_{s,t-2}$ is the measure of Chinese import competition as stated above. $\overline{\text{State}}_{s,t}$ includes state-level controls that I use in the previous specifications. For the robustness of my results, the linear time trend and the state specific linear time trend, $\phi_{s,t}$, are included in the model to control for a smooth aggregate trend and any unobservables that change smoothly within states over time. Due to the attributes of the panel data, the following results are estimated by using the fixed effects estimation, while the endogeneity of Chinese import competition measures is addressed by using the instruments stated previously.

Table 1.10: Percentages of Engineering Majors over Time

Dependent variable:	Selected industries			All industries		
Share of engineering majors	(1)	(2)	(3)	(4)	(5)	(6)
(Imports from China to U.S.)/ worker (IMP)	−0.0765* (−1.95)			0.0109 (0.66)		
IMP weighted by migration		−0.0617 (−1.56)			0.0074 (0.57)	
IMP weighted by migration and workplace			−0.0515 (−1.08)			−0.0017 (−0.16)
Linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
State linear time trend	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.168	0.187	0.202	0.201	0.206	0.208
Number of observations	561	561	561	561	561	561

Notes: Standard errors are robust to heteroskedasticity and serial correlation. t-statistics are in parentheses. The linear time trend and the state specific linear time trend are included in each specification. State-level and additional controls are also included in each column. There are 51 observations (50 states plus the District of Columbia) in each year, and the number of years in the sample is 11. The dependent variable is the percentage of engineering majors in each state over time. All imports data are in 2007 US$ and values are in thousands. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

The results in Table 1.10 are obtained by using equation 1.11 and the panel data mentioned above. The measures for Chinese import competition in columns 1-3 only use 13 NAICS industries that have a strong connection with the entire engineering field.[33] Even though the sign in each

[33] I select manufacturing industries in each round of PUMS according to the percentages of people aged 23-25 with an engineering degree. Out of the selected industries, 13 NAICS industries show up in each round of PUMS.

column is negative, only column 1 shows a significant result at the 10% level. The measures in columns 4-6, instead, use imports of all industries, but do not show any significant results.

1.7 Conclusion

This study's findings show that Chinese trade exposure has a negative effect on American students' choice of the six engineering majors (general, chemical, electrical, industrial and manufacturing, mechanical, and miscellaneous engineering). Aside from the benchmark measure of Chinese import competition, the results still hold after two alternative measures are used to account for students' potential migration to other states and the possibility of working in other states. The magnitudes of the effects range from 0.62 to 0.69 percentage point decreases in the probability of choosing the six engineering majors. I also find that males are more negatively affected by Chinese import competition in terms of the choice of the six engineering majors, while no significant results can be found if I restrict my sample to females. My results still hold firmly after I use the instruments to address endogeneity and include assorted state-level controls. I also use the average of lagged import competition to test the appropriateness of my two-year lagged measure.

For further robustness check, I carry out the falsification test and show that my results do not come from unobservables that drive both college major choice and Chinese import competition. I also use the predicted imports from the gravity model as the alternative instruments. Furthermore, I find that Chinese import competition has a positive effect on the less affected engineering majors, which could suggest that students guard themselves against the worse labor market outcomes due to Chinese trade exposure by switching to less negatively impacted engineering majors. However, I do not find my measures for Chinese import competition have a significant effect on the probability of students choosing the overall engineering fields.

CHAPTER 2

IMPORT EXPOSURE AND STEM MAJOR CHOICE: EVIDENCE FROM THE U.S.

2.1 Introduction

Science, technology, engineering, and mathematics (STEM) education has always been the focus of the U.S. education system as people in STEM fields play a vital role in the country's economic growth. The innovation of advanced technologies and the maintenance of U.S. competitiveness in the world heavily rely on their output. According to Langdon et al. (2011), the employment of STEM and non-STEM occupations grew by 7.9% and 2.6% in the 2000s, respectively. Moreover, the demand for STEM jobs is expected to keep rising for the 2020s (Zilberman and Ice 2021). College education is therefore of special importance in providing a sufficient workforce for STEM-related occupations and industries, because college majors significantly influence one's career path after graduation (Robst 2007a; Altonji et al. 2012; Lemieux 2014). To reach a balance between the demand for and supply of college graduates in STEM majors, identifying factors that could affect their choice of major is relatively important for policymakers.

An existing strand of literature extensively explores factors that influence students' decisions on their college majors such as future earnings stream (Berger 1988), expected labor market outcomes (Arcidiacono 2004; Arcidiacono et al. 2012; Baker et al. 2018; Montmarquette et al. 2002; Patnaik et al. 2020; Wiswall and Zafar 2015; Zafar 2011), family background (Leppel 2001; Ma 2009), abilities (Arcidiacono 2004; Wiswall and Zafar 2015), gender (Zafar 2013), and immigration (Orrenius and Zavodny 2015). In addition to the factors noted above, shocks to local labor markets are also associated with the choice of college major. Weinstein (2020) finds that the choice of major is influenced by sectoral-specific labor demand at the local level. Similarly, Acton (2020) shows that a decline in local employment leads to fewer students entering the relevant programs.

This paper analyzes whether trade exposure affects students' choice of STEM major through its impact on local labor markets.[1] As shown in the international trade literature, import competition from developing countries negatively impacted wages and employment at the local labor market level from the 1990s through the 2000s (Autor, Dorn, and G. Hanson 2013; Acemoglu et al. 2016). In addition, some recent papers explore the linkage between educational attainment and trade. For example, Greenland and Lopresti (2016) find that Chinese import competition increased high school graduation rates in the areas that were most impacted by trade shocks. Blanchard and Olney (2017) note that educational attainment is influenced by the composition of a country's exports. Lee (2021) examines the effect of the North American Free Trade Agreement (NAFTA) on educational attainment at the postsecondary level. Considering students' expectations of labor market outcomes while choosing a college major, import competition might affect their decisions through its effects on wages and employment. Instead of directly analyzing how changes in local labor market outcomes influence students' decisions on majors, this study looks to identify the root cause (trade exposure) that leads to changes in major choice. Wu (2020) uses this concept and finds that Chinese import competition has a significant negative effect on the probability of students choosing six engineering majors.

In this study I first present a simple theoretical model on the basis of Zafar (2011), Altonji et al. (2012), and Wiswall and Zafar (2015) to explain how trade exposure enters individuals' utility functions at the time of choosing a college major through their self-beliefs about the distribution of future labor market outcomes. The implication of the model is that the movement of people's utility considering their choice of major depends on the relationship between trade exposure and the mean of their beliefs about the distribution of labor market outcomes. The model, however, does not determine whether utility goes up or down as import competition increases. Instead, I rely on the results from the empirical section to determine the direction of utility's movement.

To quantify trade exposure at the local level, I construct my measure of trade exposure by combining the methods in Autor, Dorn, and G. Hanson (2013) and Ebenstein et al. (2011). My measure is built to specifically capture import competition faced by STEM occupations at the

[1] In this paper STEM majors include degrees in mathematics, natural sciences, engineering and related technologies, and computer/information sciences, but exclude social and behavioral sciences such as economics and psychology.

commuting zone (c-zone) level. This occupation-specific measure exploits the close relationship between STEM majors and STEM occupations and thus better gauges trade shocks.[2] I then use the National Longitudinal Survey of Youth 1997 (NLSY97) to analyze the effect of trade exposure on choice of STEM major. I find that import competition from low-income countries leads to an increase in the probability of students choosing STEM majors. The associated magnitudes of the effects are 1.05 and 0.72 percentage point increases in the probability of choosing STEM majors for college underclassmen and upperclassmen, respectively. Since the share of bachelor's degrees in STEM in 2000 is 16.4%, this implies that the 1.05 percentage point increase is equivalent to a 6.4% increase in the probability. I also explore heterogeneity across genders and find that import competition has a significant positive effect for males, but not for females regarding the choice of STEM major. In addition to NLSY97, I further use the American Community Survey (ACS) for a robustness check and similarly show that students are more likely to major in STEM due to increased trade exposure.

While it has been well recognized that STEM occupations enjoy higher wages and rapidly growing employment opportunities compared to non-STEM jobs (Fayer et al. 2017; Langdon et al. 2011), it is not clear that whether STEM occupations still maintain the competitiveness in the face of growing import competition from low-income countries. If STEM jobs can better protect people from the negative impacts brought by import competition, then students will have a greater incentive to select STEM majors. Accordingly, my next step is to use the Current Population Survey (CPS) and explore whether the local labor market outcomes (e.g., wages, employment status, and full/part-time employment) serve as channels through which trade exposure positively affects students' willingness to choose STEM majors over other fields.

The results suggest that increased import competition from low-income countries has an overall negative effect on the local labor market outcomes across STEM and non-STEM occupations from the late 1990s through the 2000s. STEM occupations, however, are less negatively affected by trade

[2] In the appendix section, Fig. B.6 shows the proportions of STEM majors working in STEM occupations by using nine waves of the National Survey of College Graduates (NSCG). For people aged below 40, at least 60% of college graduates with a degree in STEM work in STEM occupations. For people aged above 40, the proportion slightly decreases, but remains at 50%.

shocks compared to non-STEM occupations in both manufacturing and non-manufacturing sectors. For example, the 1998-2010 CPS presents that increased trade exposure decreases the weekly wages of non-STEM and STEM occupations by 1.17% and 0.62%, respectively, in the non-manufacturing sector. In addition to weekly wages, people with STEM jobs are less likely to become unemployed due to import competition as well. The CPS data indicate that increased import exposure causes the probability of unemployment for non-STEM and STEM occupations in manufacturing to increase by 0.53 and 0.24 percentage points, respectively. Aside from unemployment, I also find that STEM occupations enjoy an advantage over other jobs when a rise in trade exposure leads to a lower probability of working full-time across occupations. My results suggest that increased import exposure decreases the probability of working full-time for non-STEM and STEM occupations in manufacturing by 0.57 and 0.3 percentage points, respectively. In the non-manufacturing sector, the negative impact for STEM jobs regarding full-time employment is also smaller than that for non-STEM occupations. These results consistently imply that STEM occupations are more resistant to the negative impact brought by foreign import competition. Lastly, I use NLSY97 to explore the post-college performance of STEM and non-STEM majors in the labor market and find that increased trade exposure leads to significant negative effects for males in terms of weekly wages and employment. However, I do not observe any statistically significant effects brought by import competition when I use the pooled and female subsamples. Furthermore, the results show that STEM majors are less negatively affected by import competition for males, but not for females regarding weekly wages and employment status.

This study contributes to the existing literature in several ways. First, this paper identifies import competition as a causal factor that affects students' choice of STEM major in postsecondary education. While there are papers exploring the relationship between trade and educational attainment (Greenland and Lopresti 2016; Blanchard and Olney 2017; Lee 2021), none of them focuses on the linkage between trade and college major choice.[3] Moreover, the connection between import competition and choice of STEM major is of special importance, as the demand for skilled labor

[3] Lee (2021) briefly touches on the effect of tariff reduction on the choice of fields of study in community colleges.

from STEM fields has been rising and strong. In the 2000s, the employment of STEM jobs rose by 7.9%, while non-STEM jobs only grew by 2.6% (Langdon et al. 2011). Second, this paper shows that the differential response of STEM and non-STEM occupations to import competition regarding labor market outcomes explains why there is an increase in the probability of students choosing STEM majors due to increased trade exposure. Previous literature on trade exposure usually focuses on how wages or employment status is affected and overlooks the ensuing impact of affected labor market outcomes. However, in this study I discover that impacted labor market outcomes could be the bridge that connects import competition with choice of STEM major. Third, I use the concept of self-belief distribution to illustrate how trade exposure enters people's utility function at the time of choosing a college major. The simple utility model provides a theoretical background to depict the role of labor market outcomes in the relationship between trade exposure and choice of college major.

The rest of this chapter is organized as follows. Section 2.2 presents the theoretical model. Section 2.3 discusses the data. Section 2.4 introduces the empirical strategy. Section 2.5 offers the empirical results. Section 2.6 concludes.

2.2 Theoretical Framework

This section constructs a simple model to illustrate how trade exposure affects students' decisions on major choice. The model closely follows the works of Zafar (2011), Altonji et al. (2012), and Wiswall and Zafar (2015). There are three time periods in the model: first part of college, second part of college, and post-college labor market. By dividing the college time period into two parts, I can model the major choice that students make in different periods of college. Let t_1, t_2, and t_3 denote the three time periods, respectively. I assume that students choose their majors (m_1) in the first part of college and then make their choice again (m_2) in the second part of college. The choice of major in the second part means either switching out of or remaining in their first chosen major.

2.2.1 First Part of College

$$U_{i,m_1,t_1} = \gamma_{i,m_1} + \alpha_{i,m_1} + EU_{i,m_1}, \text{where} \tag{2.1}$$

$$EU_{i,m_1} = \beta^{t_2+t_3} \int u_i(X) dG_i(X|m_1, t_3). \tag{2.2}$$

Equation 2.1 shows the utility of individual i given the choice of college major m_1 in period t_1. Here, γ_{i,m_1} and α_{i,m_1} are individual i's preference and ability for major m_1. Since people are foresighted, their utility not only depends on own preference and ability, but also hinges on future events given their chosen fields.[4] Therefore, I use EU_{i,m_1} to capture individual i's expected utility at the time of choosing major m_1. On the RHS of equation 2.2, $\beta \in (0, 1)$ is the discount factor; $u_i(X)$ is an individual utility function that maps a vector of finite future events X to a strictly positive real number $\mathbb{R}^{++}$; and $G_i(X|m_1, t_3)$ is a self-belief distribution or joint cumulative distribution function, conditional on major m_1 in period t_3. I assume that $u(X)$ is additively separable in terms of events X for simplicity.[5] Since this paper focuses on how the effects of trade exposure on local labor markets influence students' decisions on majors, X only includes two indices of labor market outcomes given the choice of major m_1: the relative wages $\widehat{w}$ and the relative job stability $\widehat{e}$ compared to the choice of other college majors.

$$EU_{i,m_1} = \beta^{t_2+t_3} \left(\int u_i(\widehat{w}) dG_i(\widehat{w}|m_1, t_3) + \int u_i(\widehat{e}) dG_i(\widehat{e}|m_1, t_3) \right) \tag{2.3}$$

$$= \beta^{t_2+t_3} \left[E\left(u_i(\widehat{w})\right) + E\left(u_i(\widehat{e})\right) \right]. \tag{2.4}$$

Because of the separability and additivity assumptions imposed on the utility function, equation 2.2 can be written as equation 2.3. Moreover, $G_i(x|m_1, t_3)$ with $x \in \{\widehat{w}, \widehat{e}\}$ is a marginal self-belief distribution, or marginal cumulative distribution function, with respect to each event x. Furthermore, EU_{i,m_1} can be expressed as the summation of expected utility of the two labor market outcomes as shown by equation 2.4. To introduce trade exposure ξ into the model, I assume that the

[4] Here, I assume that people only care about post-graduation events that happen in t_3 when choosing majors.

[5] The assumption of additive separability implies that only the marginal self-belief distribution matters for expected utility, while the joint distribution of beliefs does not enter the equation of expected utility (Zafar 2011).

mean of $G_i(x|m_1, t_3)$ is a fucntion of trade exposure $\mu_i^x(\xi)$.[6] Students' beliefs about the distribution of labor market outcomes change to $G_i^*(x|m_1, t_3)$ with the new mean $\mu_i^x(\xi^*)$ after experiencing increased trade exposure. The expected utility that uses the new marginal self-belief distribution $G_i^*(x|m_1, t_3)$ is denoted by EU_{i,m_1}^*.

$$U_{i,m_1,t_1}^* - U_{i,m_1,t_1} = \beta^{t_2+t_3} \left\{ [E^*(u_i(\widehat{w})) - E(u_i(\widehat{w}))] + [E^*(u_i(\widehat{e})) - E(u_i(\widehat{e}))] \right\} \qquad (2.5)$$

To see how increased trade exposure affects students' utility when choosing majors, equation 2.5 shows that the change in utility equals the summation of differences between expected utility before and after experiencing increased trade exposure. If the differences are positive (negative) for both labor market outcomes, students are expected to find a job with relatively higher (lower) wages and stability by choosing major m_1. Therefore, students are more (less) likely to choose major m_1 due to increased trade exposure. However, if the two differences share different signs, then the effect of increased trade exposure on students' decisions on major m_1 will be ambiguous.

The question is: Who will change their decisions on college majors due to increased trade exposure? Here, I use Fig. B.1 to illustrate two scenarios. Suppose that college majors are classified into two categories: STEM and non-STEM majors. The horizontal axis represents the relative utility of choosing a STEM major ($U_{stem}/U_{nonstem}$), while the vertical axis is the frequency of students. For students with relative utility greater (smaller) than 1, they will choose STEM (non-STEM) majors. The black bell curve is the frequency distribution of relative utility before experiencing a rise in trade exposure. If an increase in trade exposure results in relatively better labor market outcomes for STEM majors and therefore higher relative utility $U_{stem}/U_{nonstem}$, then the black bell curve is expected to shift to the right, as shown by the green bell curve in the left panel of the figure. The red shaded area between the two bell curves implies the share of people who change their minds and decide to choose STEM majors due to increased trade exposure. On the other hand, if increased trade exposure leads to relatively worse labor market outcomes for STEM majors and thus lower relative utility $U_{stem}/U_{nonstem}$, the black bell curve will shift to the left, as

[6]For simplicity, the variance of $G_i(x|m_1, t_3)$ is assumed to be fixed.

shown by the green bell curve in the right panel. The blue shaded area between the two bell curves represents the share of people who originally decide to choose STEM majors but end up choosing non-STEM majors because of increased trade exposure.

This model, however, does not explicitly decide whether utility conditional on a major increases or decreases, because of increased trade exposure. Instead, the direction in which utility moves relies on results from the empirical section to determine the relationship between trade exposure ξ and the mean of the self-belief distribution μ_i^x. Figure B.2 uses $G_i(\cdot)$ and $G_i^*(\cdot)$ to illustrate the relationships between ξ and μ_i^x.[7] The green and black lines in the figure, respectively, represent the self-belief distribution before and after experiencing increased trade exposure. An increase in trade exposure results in a smaller mean for $G_i^*(\cdot)$ in the left panel, but a larger mean for $G_i^*(\cdot)$ in the right panel.

2.2.2 Second Part of College

Subsection 2.2.1 has displayed the effect of trade exposure on the utility function in the first part of college. Following the similar concept in the previous subsection, I briefly describe how a student's utility function is influenced in the second part of college.

$$U_{i,m_2,t_2} = \gamma_{i,m_2} + \alpha_{i,m_2} + \beta^{t_3}\left[\sum_{x\in\{\widehat{w},\widehat{e}\}} \int u_i(x(\xi))dG_i(X|m_1,m_2,t_3)\right]. \tag{2.6}$$

Equation 2.6 is individual i's utility in period t_2 given the choice of major m_2. γ_{i,m_2} and α_{i,m_2} are the preference and ability for major m_2 of individual i. Here, m_2 can either be different from or identical to m_1 since students decide whether to stay in their first chosen field in period t_2. The self-belief distribution $G_i(X|m_1,m_2,t_3)$ is not only conditional on the new major m_2 but also on the first chosen major m_1 as the knowledge and skills learned in the previous major continue to influence one's belief about the distribution of labor market outcomes. While the self-belief

[7]For simplicity, I make an assumption that $G_i^*(\cdot)$ either first-order stochastically dominates $G_i(\cdot)$, or $G_i^*(\cdot)$ is first-order stochastically dominated by $G_i(\cdot)$. The assumption implies either $G_i^*(\cdot) \leq G_i(\cdot)$ or $G_i^*(\cdot) \geq G_i(\cdot)$ for all realized values of labor market outcomes.

distribution slightly changes, the conclusion remains the same: the direction in which utility moves depends on the relationship between trade exposure ξ and the mean of the self-belief distribution μ_i^x.

2.3 Data

The main dataset I use is the National Longitudinal Survey of Youth 1997 (NLSY97), which is a panel dataset that has a sample of 8984 respondents who were 12-17 years old in 1997. The survey was conducted annually from 1997 through 2011 and became biennial after 2011. The dataset contains detailed information regarding respondents' education, family background, demographics, and labor market outcomes. For example, NLSY97 provides information on wages, occupation titles, industries, and college majors that respondents chose during each semester in college. To analyze the effects of trade exposure on students' decisions on choice of college majors, I restrict the sample to respondents who attended college and had information on college majors and migration history.[8] Moreover, I only focus on major choices that respondents made in the college they first attended.

Aside from the NLSY97, I also use the 2009-2017 American Community Survey (ACS) to analyze the effects of trade exposure on choice of major. ACS collects roughly 1% of the American population every year and has had respondents with bachelor's degrees or above report their fields of bachelor's degree since 2009. For comparability of the results from the two different datasets, I restrict my sample from ACS to those who were aged 23-27 at the time of survey and assume that people go to college at age 18. Therefore, most respondents in the ACS sample were first attending college in the 2000s as in NLSY97 by imposing the assumption.[9]

Table 2.1 presents the descriptive statistics of NLSY97 and ACS 2009-2017. From the table, we see that different genders show differential trends of choosing STEM and non-STEM majors. In NLSY97, of the 19.3% of people who chose STEM, 69.4% (13.4/19.3) of them are males, while

[8]"College" here refers to both 2-year and 4-year colleges.

[9]Note that people with associates' degrees are not included in the ACS sample. Most respondents in NLSY97 first attended college before 2010. To get similar cohorts from ACS 2009-2017, I therefore restrict the sample in ACS to respondents aged 23-27.

Table 2.1: Descriptive Statistics

	NLSY97	ACS 2009-2017
STEM: (%)	19.3	20.5
Male	13.4	12.4
Female	5.9	8.1
Non-STEM: (%)	80.7	79.5
Male	33.6	30.7
Female	47.1	48.8
Year of first college attendance: (%)		
before 2000	14.9	N/A
2000-2010	79.7	N/A
after 2010	5.4	N/A
N	5,495	431,428

Notes: Observations are weighted using personal weights. The sample from ACS is restricted to people aged 23-27 in each round of survey. Year of first college attendance refers to the year when a person first attended college. STEM majors include degrees in mathematics, natural sciences, engineering and related technologies, and computer/information sciences, but exclude social and behavioral sciences such as economics and psychology.

females only account for 30.6% (5.9/19.3). The dominance of males in STEM is also observed in ACS 2009-2017. However, females become the majority in non-STEM fields. For instance, females make up 58.4% (47.1/80.7) and 61.4% (48.8/79.5), respectively, in NLSY97 and ACS.[10] The table also shows that 94.6% of respondents in NLSY97 first attended college before 2010, and only 5.4% of people went to college after 2010.

In the appendix, I use data from the National Center for Education Statistics (NCES) to show the trend of STEM majors. Figure B.3 presents the share of bachelor's degrees in STEM fields and suggests that the proportion slightly fluctuates between 15% and 17%. In addition, Fig. B.4 demonstrates the geographical variation of bachelor's degrees in STEM in 2003-04 and 2013-14. Aside from changes in the shares of majors, Table B.3 reports the proportions of each field in STEM occupations by using ACS 2009-2017. As shown in the table, at least 60% of college graduates in STEM occupations possess a degree in STEM majors.

In addition to NLSY97 and ACS, I also employ data from different sources to construct my measure for trade exposure and its corresponding instrumental variable. I use trade data from

[10] I also show the shares of degree fields for underclassmen and upperclassmen across genders in Table B.2.

the United Nations Comtrade Database (UN comtrade) and Schott (2008) and also use Integrated Public Use Microdata Sample (IPUMS) 1990 to calculate the shares of each STEM occupation across industries. For local employment shares in my measure, I utilize the imputed county-level data from Eckert et al. (2020a) and further employ 1998-2010 Current Population Survey (CPS) monthly data to examine the effects of trade exposure on labor market outcomes. In the appendix, Fig. B.5 depicts the geographic distribution of STEM occupations in 2001 and 2012. The maps suggest a pronounced increase in the shares of STEM occupations in most states.

2.4 Empirical Strategy

2.4.1 Measure of Trade Exposure

To quantify the magnitude of trade exposure, I refer to the measures in Autor, Dorn, and G. Hanson (2013) and Ebenstein et al. (2011).

$$\mathrm{IMP}_{s,t^-} = \sum_{k\in K}\sum_{j\in J}\frac{L_{k,j,90}}{L_{k,90}}\left(\frac{L_{s,j,t^-}}{L_{j,t^-}}\frac{import^{low}_{j,t^-}}{L_{s,t^-}}\right). \tag{2.7}$$

Equation 2.7 shows my measure for trade exposure. This study primarily focuses on STEM fields, and K is the set of occupations that are closely related to STEM majors such as mathematicians, technicians, engineers, and scientists. I classify these occupations as STEM occupations.[11] Moreover, J is the set of 4-digit NAICS industries; t is the year when respondents first attended college; s stands for local labor markets and represents different levels across NLSY97, ACS, and CPS; and s is c-zones in NLSY97, but defined as states of birth and states of work in ACS and CPS, respectively. Since it takes time for trade exposure to influence local labor market outcomes and then to indirectly affect students' choice of college major, I use the lagged measure of trade exposure and t^- refers to lagged time periods, while $import^{low}_{j,t^-}$ represents U.S. imports of industry j from low- and lower-middle income countries (henceforth low-income countries) in period t^-.[12]

[11] For a complete list of STEM occupations that I select, please refer to Table B.1.

[12] I combine low-income and lower-middle-income countries together and classify them as the low-income group according to their gross national income (GNI) per capita in 2000: a country belongs to the low-income group if its

In the appendix, Fig. B.7 shows the geographical distribution of trade exposure between 2000 and 2010 by using this measure.

The fractions inside the parentheses come from Autor, Dorn, and G. Hanson (2013), emphasizing trade exposure faced by U.S. local labor markets; L_{s,j,t^-} is the employment of industry j in local labor market s; L_{j,t^-} stands for the total employment of industry j in the U.S.; and L_{s,t^-} refers to the working age population in s. To derive these employment variables, I use the averages of lagged local employment.[13] Here, $\frac{L_{s,j,t^-}}{L_{j,t^-}}$ suggests the relative importance of local labor market s for industry j compared to other areas. For example, Chicago is one of the most important hubs of food manufacturing industries in the U.S., and thus $L_{Chicago,food,t^-} / L_{food,t^-}$ should be relatively larger than other places. The fraction outside of the parentheses comes from Ebenstein et al. (2011), stressing the relative importance of each industry for occupation k. $L_{k,j,90}$ is the number of workers in occupation k and in industry j, while $L_{k,90}$ is the total number of workers in occupation k. I use IPUMS 1990 to calculate the fraction.[14]

Even though this measure seems complicated, it has an intuitive interpretation: trade exposure faced by STEM occupations across local labor markets. Here, I provide an example to illustrate how my measure works. Suppose that there are only two industries (auto and clothing) and one STEM occupation (engineers) in Michigan for simplicity. Assume that import competition is \$100/person and \$50/person for the auto and clothing industries, respectively. If 80% of engineers work in the auto industry while the remaining 20% work in the clothing industry, then import competition faced by engineers in Michigan will be \$90/person according to my measure.[15] In the example since most engineers work in the auto industry, import competition faced by engineers is weighted by the distribution of engineers across the two industries to account for the relative importance of each industry.

In addition, my measure of trade exposure inherits two traits from its original measures. First,

GNI per capita in 2000 was below \$755; a country belongs to the lower-middle-income group if its GNI per capita in 2000 was between \$755 and \$2994.

[13]For example, if t^- was 2000, I use the averages of local employment from 1996 through 2000.

[14]The sample of IPUMS 1990 is restricted to college graduates who were aged 23-30 at the time of the survey.

[15] $\$100 \times 80\% + \$50 \times 20\% = \$90$.

this measure is occupation-specific; i.e., specific to the group of STEM occupations. This trait helps me better gauge the effects of import competition on labor market outcomes of those STEM jobs and more precisely evaluate how the choice of STEM major is affected. Second, it captures differential intensities of import competition encountered by STEM occupations across local labor markets. For example, mechanical engineers of the automotive industry in Michigan should experience stronger import competition than their counterparts in North Carolina. By introducing $\frac{L_{s,j,t^-}}{L_{j,t^-}}$ into my measure, it need not be assumed that STEM occupations experience the same intensity of trade exposure across the U.S.

2.4.2 Instrumental Variable

My measure of trade exposure uses imports from low-income countries to capture their productivity growth. However, an increase in imports can come from either America's own demand for foreign products (demand driven) or productivity growth of foreign countries (supply driven). To correctly estimate the impact of trade exposure on STEM occupations in local labor markets, I need to identify the supply driven part of imports, thus employ the instrumental variable in Autor, Dorn, and G. Hanson (2013), and construct a similar instrument.

$$\mathrm{IMP}^{Other}_{s,t^-} = \sum_{k\in K}\sum_{j\in J}\frac{L_{k,j,90}}{L_{k,90}}\left(\frac{L_{s,j,t^- -5}}{L_{j,t^- -5}}\frac{import^{Other}_{j,t^-}}{L_{s,t^- -5}}\right). \tag{2.8}$$

Equation 2.8 shows my instrumental variable for the measure in equation 2.7. Here, $import^{Other}_{j,t^-}$ refers to eight high-income countries' imports from the low-income countries defined above.[16] The instrumental variable uses 5-year lagged (relative to t^-) employment to prevent underestimation of the effects of import competition on local labor market outcomes, because affected industries' contemporary employment might be lower due to trade shocks.[17]

[16] The eight high-income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[17] If t^- is two-year lagged, then $t^- - 5$ is seven-year lagged relative to t. In addition, I use single-year values for employment variables in the instrument.

2.4.3 Labor Market Outcomes

As noted in section 2.2, I first need to identify whether the relative labor market outcomes of STEM majors become better or worse due to increased trade exposure, so the relationship between trade exposure and the mean of students' self-belief distribution can be established. If a rise in trade exposure results in relatively better (worse) labor market outcomes of STEM majors, then the mean of students' self-belief distribution of relative labor market outcomes is expected to increase (decrease). Due to the data constraints on the labor market outcomes of STEM majors in the 2000s, I use the CPS data and treat the performance of STEM occupations as a proxy for the labor market outcomes of STEM majors.[18] In addition, I use NLSY97 to explore whether people who chose STEM majors in college outperform others in the labor market when facing increased trade exposure.

In this subsection, I propose some proxies for $\widehat{w}$ (relative wages) and $\widehat{e}$ (relative job stability) so that the relationship between trade exposure and the relative labor market outcomes of STEM majors can be evaluated in the empirical section. For relative wages, I use $\widehat{w}_{stem\_occ} = \frac{w_{stem\_occ}}{w_{other\_occ}}$, where w_{stem_occ} is the wages of STEM occupations, and w_{other_occ} is the wages of other occupations. An increase in $\widehat{w}_{stem\_occ}$ implies that STEM occupations offer relatively higher wages than other occupations. As for relative job stability, I use $\widehat{u}_{stem\_occ} = \frac{1-Pr(u)_{stem\_occ}}{1-Pr(u)_{other\_occ}}$, where $Pr(u)_{stem\_occ}$ is the probability of unemployment for STEM occupations, and $Pr(u)_{other\_occ}$ is the probability of unemployment for other occupations. An increase in $\widehat{u}_{stem\_occ}$ suggests that non-STEM occupations are more likely to encounter unemployment. In addition, I also use $\widehat{full}_{stem\_occ} = \frac{Pr(full)_{stem\_occ}}{Pr(full)_{other\_occ}}$, where $Pr(full)_{stem\_occ}$ refers to the probability of working full time for STEM occupations, and $Pr(full)_{other\_occ}$ is the probability of working full time for other occupations. An increase in $\widehat{full}_{stem\_occ}$ suggests people with STEM jobs are more likely to work full time compared to non-STEM occupations.

[18] In the theoretical model, $\widehat{w}$ and $\widehat{e}$ refer to labor market outcomes of a major instead of an occupation. However, since STEM majors and STEM occupations share a close relationship, the performance of STEM occupations can be considered an important factor in students' choice of STEM major. In the appendix, Fig. B.6 shows the proportions of STEM majors working in STEM occupations and suggests at least 50% of people with a degree in STEM work in STEM occupations.

2.4.4 Econometric Specifications

This subsection presents econometric specifications for testing the effects of trade exposure on students' choice of STEM major and labor market outcomes (relative wages and job stability).

$$\text{STEM}_{ist} = \alpha + \beta \text{IMP}_{s,t^-} + \text{Individual}_i \rho + T \times \phi_s + \phi_{s,97} + \varepsilon_{ist}. \tag{2.9}$$

Equation 2.9 is my baseline specification for estimating the effects of trade exposure on choice of STEM major by using NLSY97. I use a linear probability model to carry out my estimation. The dependent variable STEM_{ist} is equal to 1 if individual i first attended college in year t and chose a STEM major and equal to 0 otherwise.[19] IMP_{s,t^-} is import competition faced by c-zone s in lagged time period t^-, and c-zone s is where individual i lived during t^-.[20] Here, I use the average of one-year and two-year lagged measures of trade exposure in subsection 2.4.1.[21] Individual_i includes assorted individual characteristics that were fixed at the time of choosing college major such as parents' educational levels, genders, races, college types (2-year or 4-year), and whether respondents are foreign-born. To prevent personal preferences and abilities from causing bias in my estimates, I also include respondents' GPAs in high school to partially control for abilities at STEM majors. To control for preferences toward STEM majors, I include several dichotomous variables regarding whether they took biology, chemistry, physics, general math, advanced math, and computer programming courses in high school. I also include birth years to control for unobserved factors that could influence different cohorts' decisions on major choice, such as policies by the U.S. Department of Education or national budget for STEM fields. Standard errors are clustered on c-zone to allow for serial correlation among individuals within each c-zone. $T \times \phi_s$ is the c-zone specific linear time trend, which controls for any time-varying unobservables in c-zones such as changes in the local education system and educational resources. Here, $\phi_{s,97}$ refers

[19] I use years when students first attended college instead of years when students chose their majors. Since prerequisites for each major differ across colleges, using enrollment years is more consistent.

[20] I use the crosswalk from Autor, Dorn, and G. H. Hanson (2013) to convert counties into commuting zones.

[21] In the appendix, Table B.4 shows the effects of import competition using one-, two-, and three-year lagged measures.

to respondents' c-zones in the first round of NLSY in 1997 and is added to the model to control for time-invariant unobservables such as geographical features or cultural factors, while ε_{ist} is the error term.

$$\text{STEM}_{ist} = \alpha + \beta \text{IMP}_{s,t^-} + \text{Individual}_i \rho + T \times \phi_s + \phi_s + \varepsilon_{ist}. \tag{2.10}$$

For ACS data, I use equation 2.10 to estimate the effects of trade exposure on choice of STEM major. Since ACS does not have information on migration history and time of college enrollment, I assume that all respondents with a bachelor's degree or above first attended college at 18 years old and that people stayed in their states of birth before attending college. STEM_{ist} is still a binary variable and equal to 1 if individual i who was born in state s possessed a bachelor's degree in STEM. t is the year when respondents were 18 years old. IMP_{s,t^-} is the average of one-year and two-year lagged measures of trade exposure, but measures trade exposure faced by individual i's state of birth s. Individual_i includes only genders and races due to data constraints. $T \times \phi_s$ is the state-specific linear time trend to control for unobserved time-varying factors in respondents' states of birth, while ϕ_s is the state of birth fixed effect. Standard errors are clustered on state of birth to allow for serial correlation among individuals within states.

$$\begin{gathered} Outcomes^{cps}_{ijkst} = \alpha + \beta \text{IMP}_{s,t^-} + \gamma \text{IMP}_{s,t^-} \times 1_{stem\_occ} + \text{Individual}_i \rho \\ T \times \phi_s + \phi_s + \phi_j + \phi_k + \varepsilon_{ijkst}. \end{gathered} \tag{2.11}$$

Equation 2.11 is the baseline specification for estimating the effects of trade exposure on labor market outcomes by using the CPS data. $Outcomes^{cps}_{ijkst}$ represents three dependent variables that I will use for estimation: $Outcomes \in \{log(\text{wages}), \text{Unemployed}, \text{Full-time}\}$. $log(\text{wages}_{ijkst})$ is the log weekly wages (values in 2007 US$) of individual i whose occupation was k and worked in industry j in state s in year t. $\text{Unemployed}_{ijkst}$ is a binary variable and equal to 1 if individual i was unemployed in year t. Full-time_{ijkst} is also a binary variable and equal to 1 if individual i was a full-time employee in year t. IMP_{s,t^-} is the average of one-year and two-year lagged measures of trade exposure and gauges trade exposure encountered by individual i's state of work s. 1_{stem_occ} is an indicator variable and equal to 1 if individual i's job belongs to STEM occupations. The coefficient β measures the effects of trade exposure on the three labor market outcome variables for non-STEM occupations, while γ measures the relative effects of trade exposure for STEM occupations compared to non-STEM occupations. By comparing the signs of estimated β and γ, I am able to know whether the impact of trade exposure is larger or smaller for STEM occupations relative to non-STEM occupations. For instance, if the dependent variable is $log(\text{wages}_{ijkst})$ and the signs are negative for the estimated β, but positive for the estimated γ, then it implies that STEM occupations are less negatively affected by rising import exposure in terms of weekly wages. Accordingly, the proxy for relative wages of STEM occupations $\widehat{w}_{stem\_occ} = \frac{w_{stem\_occ}}{w_{other\_occ}}$ will increase due to trade exposure. This also implies the mean of people's self-belief distribution of relative weekly wages for STEM majors becomes larger according to my assumption. Similarly, the relationship between trade exposure and other labor market outcomes such as employment status or full-/part-time employment can also be determined by examining the estimates of β and γ.

Individual$_i$ contains educational levels, potential experience, and its square, genders, and races.[22] Moreover, I divide respondents in the sample into six age cohorts and include the cohort fixed effect.[23] I further add assorted time trend and fixed effects, including the state-specific linear time trend $T \times \phi_s$, the state of work fixed effect ϕ_s, the industry fixed ϕ_j, and the occupation fixed effect ϕ_k. Standard errors are clustered on the state×cohort to allow for serial correlation among people of the same cohort within states.

$$\begin{aligned} Outcomes_{ijkst}^{nlsy} = \alpha + \beta \text{IMP}_{s,t^-} + \gamma \text{IMP}_{s,t^-} \times 1_{stem} + \text{Individual}_i \rho + \\ T \times \phi_s + \phi_{s,97} + \phi_j + \phi_k + \varepsilon_{ijkst}. \end{aligned} \tag{2.12}$$

In addition to CPS, I use NLSY97 to explore whether people who chose STEM majors in college outperform others in the labor market when facing increased trade exposure. Equation 2.12 is the

[22]Potential experience is derived by substracting years of education from respondents' ages.

[23]The age cohorts are based on respondents' years of birth: 1941-1950, 1951-1960, 1961-1970, 1971-1980, 1981-1990, and 1991-2000.

baseline specification for the estimation. $Outcomes^{nlsy}_{ijkst}$ includes two labor market outcomes as noted above: log(wages) and Unemployed. IMP_{s,t^-} is the average of one-year and two-year lagged trade exposure encountered by individual i's c-zone s. 1_{stem} is an indicator variable and equal to 1 if individual i chose a STEM major in college. Individual_i contains personal characteristics such as races, genders, birth years, majors in the first and second parts of college, parents' educational levels, and potential experience and its square. The c-zone linear time trend, the location, the industry, and the occupation fixed effects are also included to control for unobservables. Standard errors are clustered at the c-zone level.

2.5 Results

2.5.1 Major Choice

Table 2.2: Baseline Estimates - NLSY97

	OLS			2SLS		
	Under (1)	Upper (2)	Upper (3)	Under (4)	Upper (5)	Upper (6)
(Imports from *low income* to U.S.)/worker (IMP)	0.0427*	0.0722***	0.0415**	0.085**	0.1185***	0.0585***
	(0.025)	(0.019)	(0.018)	(0.035)	(0.030)	(0.020)
Control for choice of major in the first part	No	No	Yes	No	No	Yes
Estimated effects (pp)	0.53	0.89	0.51	1.05	1.47	0.72
Number of observations	5,495	5,495	5,495	5,495	5,495	5,495
				First stage		
(Imports from *low income* to *Other*)/worker (IMP^{other})				1.0562***	1.0562***	1.0561***
				(0.183)	(0.183)	(0.183)
$F-Stat$				33.3	33.3	33.46

Notes: "Under" and "Upper" refer to choices of major for college underclassmen and upperclassmen. Estimated effects are in percentage points and computed as coefficient×0.45 (ΔIMP)×0.275 (share of supply driven imports). Standard errors in parentheses are robust to heteroskedasticity and clustered on the c-zone. C-zone linear time trend, c-zone 1997 fixed effect, and cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Table 2.2 shows the baseline OLS and 2SLS estimates by using equation 2.9. "Under" and "Upper" in the column headers represent the major choices of college underclassmen and upperclassmen.[24] Corresponding to the theoretical model in section 2.2, underclassmen and upperclassmen

[24] In NLSY97, I use respondents' first and last reported majors as their choices of major in the first and second parts

refer to students who are in the first and second parts of college, respectively.[25] Columns 1 and 2 suggest that trade exposure has a positive effect on the choices of STEM majors for both college underclassmen and upperclassmen, and the results are statistically significant at the 10% and 1% levels, respectively. However, since the choice of major in the first part of college could imply one's preference as well as ability, the estimation for the choice in the second part likely is biased without including the first-part major choice. Column 3 presents the result after the specification is controlled for the first-part choice of major, and that the estimated coefficient is still significant at the 5% level. On the other hand, the OLS estimates could be biased due to the measure of trade exposure capturing both supply and demand driven imports from low-income countries.

To tackle the endogeneity of the measure, I use the instrument in subsection 2.4.2. Columns 4-6 show the 2SLS results and the corresponding first-stage estimates. Column 4 reports that trade exposure has a positive effect on college underclassmen's choice of STEM major. The estimated coefficient on IMP is 0.085, which is significant at the 5% level and much larger than the OLS counterpart in column 1. Since the increase in IMP is \$450 per person from the late 1990s through the 2000s (i.e., ΔIMP = \$450) and the share of supply-driven component of imports is 0.275, the coefficient is associated with a 1.05 percentage point increase in the probability of choosing STEM majors.[26] In addition, the share of bachelor's degrees in STEM in 2000 is 16.4%, which implies that the 1.05 percentage point increase is equivalent to a 6.4% increase in the probability.[27] Columns 5-6 report that trade exposure also has a positive effect on the choice of STEM major for college upperclassmen, but the magnitude of the effect decreases if the specification is controlled for students' choice of major in the first part of college. The coefficient in column 6 suggests an associated 0.72 percentage point, or equivalently 4.39%, increase in the probability of choosing STEM majors.[28]

of college.

[25] Conceptually, the first and second parts represent the first and last two years of a four-year college, while the first and second parts refer to the first and second years of a two-year college.

[26] $0.45 \times 0.275 \times 0.085 \approx 0.0105$. Please see Appendix B.1 for the derivation of supply-driven component of imports.

[27] $1.05\%/16.4\% \approx 6.4\%$. The share of bachelor's degrees in STEM is from NCES.

[28] $0.45 \times 0.275 \times 0.0585 \approx 0.72\%$. $0.72\%/16.4\% \approx 4.39\%$.

Table 2.2 uses the preferred specification: the linear probability model with the c-zone specific linear time trend. For a robustness check, Table B.5 in the appendix presents the results of the linear probability and probit models, which use year fixed effects instead and control for the numbers of college graduates of STEM fields and the employment of STEM related industries.[29] Columns 1 and 2 of Table B.5 suggest that the magnitudes of estimates are slightly smaller but still significant. For the probit model, columns 3 and 4 show that import competition has a stronger effect for upperclassmen than for underclassmen since only the estimate in column 4 is statistically significant. Comparing the average partial effect, 0.0607, in column 4 with the estimate, 0.0585, in column 6 of Table 2.2, I find that these two numbers are qualitatively similar. For the rest of this paper, I would use the linear probability model with c-zone (state) specific linear time trend as my preferred specification.

The results in Table 2.2, however, seem to be inconsistent with the findings in Lee (2021) since Lee (2021) finds that a reduction of tariffs leads to a higher completion rate for fields unrelated to manufacturing (e.g., health professions security, and protective services, and family and consumer sciences) , but not for fields related to manufacturing (e.g., precision production, engineering technologies, transportation, and mechanic and repair technologies). There are several potential explanations for the difference. First, we look at different time periods. This study focuses on the period of 2000s, while Lee (2021) explores the impact of the free trade agreement between the US and Mexico from 1990 through 2001. Second, my measure of trade exposure is based on imports from low-income countries, whereas Lee (2021) uses tariff reductions as the measure of trade liberalization. Third, the definition of STEM in this paper is greatly different from "upskill" defined in Lee (2021).[30] Lastly, NLSY97 includes students enrolled in either community colleges or four-year universities, while Lee (2021) focuses on students in community colleges.

Since males and females might respond differently to increased import competition, I divide

[29]The numbers of college graduates are at the c-zone level. The employment of STEM related industries is also at the c-zone level. The STEM related industries include manufacturing excluding food industries (codes 32-33), information (code 51), and professional, scientific, and technical services (code 54). I use the two-step control function approach to tackle endogeneity for the probit model.

[30]Upskill refers to the fields of study that are related to manufacturing.

Table 2.3: 2SLS Estimates by Gender - NLSY97

	Underclassmen			Upperclassmen		
	Pooled (1)	Males (2)	Females (3)	Pooled (4)	Males (5)	Females (6)
(Imports from *low income* to U.S.)/worker (IMP)	0.085**	0.1248**	0.0252	0.0585***	0.0853**	0.0027
	(0.035)	(0.051)	(0.043)	(0.020)	(0.038)	(0.020)
Estimated effects (pp)	1.05	1.54	0.31	0.72	1.06	0.03
Number of observations	5,495	2,501	2,994	5,495	2,501	2,994

Notes: The choice of major in the first part of college is included as a control in the specifications of columns 4-6. Standard errors in parentheses are robust to heteroskedasticity and clustered on the c-zone. C-zone linear time trend, c-zone 1997 fixed effect, and cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

NLSY97 into two subsamples by gender to explore heterogeneity of choice of STEM major across genders. Table 2.3 presents the results by gender: males and females. The estimates in columns 1 and 4 are the baseline results from columns 4 and 6 of Table 2.2. Columns 2 and 3 suggest that trade exposure leads to significant positive effects on the choice of STEM major for male underclassmen, but not for females. The associated effect is a 1.54 percentage point increase in the probability of choosing a STEM major for male underclassmen. The estimate in column 5 is significant at the 5% level and associated with a 1.06 percentage point, or 6.46%, increase in the probability of male upperclassmen choosing STEM major.[31] The insignificant coefficient in column 6 indicates that the choice of STEM major for female upperclassmen is not influenced by import competition from low-income countries.

According to the results in Table 2.3, I find that males are more likely to be impacted by increased trade exposure from low-income countries in terms of the choice of STEM major. Since I assume that trade exposure affects students' choice through its effect on local labor market outcomes, this finding might also resonate with the implication of Zafar (2013) that males care more about the pecuniary outcomes in the workplace than females. Moreover, the findings in the next subsection in which the positive benefit of working in STEM occupations is not statistically significant for younger females (aged 23-40) regarding weekly wages and full-time employment, could also explain the insignificant results for females in Table 2.3. Some papers in the related literature similarly observe

[31] $1.06\%/16.4\% \approx 6.46\%$.

that females experience smaller impacts from trade. For example, Blanchard and Olney (2017) find that low-skill-intensive manufactured exports have a larger negative effect on the years of schooling for males than for females. In Lee (2021), the enrollment effect for community colleges is stronger in commuting zones with lower proportions of females.

Table 2.4: 2SLS Estimates by Year of College Attendance - NLSY97

	Underclassmen			Upperclassmen		
	1997-2010 (1)	2000-2010 (2)	2000-2007 (3)	1997-2010 (4)	2000-2010 (5)	2000-2007 (6)
(Imports from *low income* to U.S.)/worker (IMP)	0.1183**	0.1584**	0.1064*	0.0749**	0.0666**	0.0854**
	(0.060)	(0.065)	(0.056)	(0.029)	(0.032)	(0.034)
Estimated effects (pp)	1.46	1.96	1.32	0.93	0.82	1.06
Number of observations	5,192	4,414	4,045	5,192	4,414	4,045

Notes: The choice of major in the first part of college is included as a control in the specifications of columns 4-6. Standard errors in parentheses are robust to heteroskedasticity and clustered on the c-zone. C-zone linear time trend, c-zone 1997 fixed effect, and cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Trade exposure might have differential impacts on local labor markets and on occupational outcomes in different time periods. Therefore, I divide NLSY97 into three subsamples according to respondents' years of first college attendance. Table 2.4 reports the results by period: 1997-2010, 2000-2010, and 2000-2007. As noted in Table 2.1, around 95% of respondents in NLSY97 first attended college in the period of 1997-2010. Columns 1-3 show that trade exposure has a positive effect on the choice of STEM major for college underclassmen in each time period, and that the largest positive effect of trade exposure occurred in the period 2000-2010. The estimate in column 2 is significant at the 5% level and is associated with a 1.96 percentage point, or equivalently 11.95%, increase in the probability of underclassmen choosing STEM majors.[32] In column 3, the significance level decreases to 10%, but the estimate still indicates that college underclassmen are 8.05% more likely to choose STEM majors.[33] For college upperclassmen's choice of major in columns 4-6, even though the magnitudes of the coefficients are relatively smaller compared to their counterparts in columns 1-3, the coefficients in columns 4-6 are significant at the 5% level. In

[32] $1.96\%/16.4\% \approx 11.95\%$.
[33] $1.32\%/16.4\% \approx 8.05\%$.

addition, upperclassmen's choice of STEM major is most positively affected by import competition from low-income countries in the period 2000-2007. The estimate in column 6 implies that college upperclassmen are 6.46% more likely to choose STEM fields as their choice of majors.[34]

Table 2.5: 2SLS Estimates by Gender and Year of First College Attendance - ACS

		Gender		Year of attendance	
	Pooled (1)	Males (2)	Females (3)	2000-2010 (4)	2000-2007 (5)
(Imports from *low income* to U.S.)/worker (IMP)	0.0598*** (0.023)	0.0882** (0.036)	0.0435 (0.027)	0.0730*** (0.026)	0.0683*** (0.018)
Estimated effects (pp)	0.74	1.09	0.54	0.90	0.85
Number of observations	431,428	182,381	249,047	403,902	282,305

Notes: I assume that people attend college at age 18. Year of college attendance refers to the year when a respondent is 18 years old. Standard errors in parentheses are robust to heteroskedasticity and clustered on state of birth. State linear time trend and state of birth fixed effect are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

For a robustness check of the NLSY97 results, I further use ACS data to estimate the effects of import competition on students' choice of STEM major. However, the results obtained from using ACS data should be interpreted with caution, since ACS data are lacking in detailed personal information that could be used to control for unobservables. Table 2.5 shows the results by using equation 2.10. Column 1 suggests that trade exposure leads to a significant positive effect on students' choice of STEM major. The estimate 0.0598 is associated with a 0.74 percentage point, or 4.5%, increase in the probability of students choosing STEM majors.[35]

To explore heterogeneity across genders, I divide the sample into male and female subsamples. The estimate in columns 2 is associated with a 1.09 percentage point increase in the probability of choosing STEM majors for male students. However, column 3 suggests that trade exposure does not have a statistically significant effect for females regarding choice of STEM major. Besides exploring heterogeneity across genders, I also estimate the sample across different time periods based on respondents' potential years of first college attendance. Since ACS data do not have information on the year of college enrollment, I assume that people first attend college at age 18.

[34] $1.06\%/16.4\% \approx 6.46\%$.

[35] $0.74\%/16.4\% \approx 4.5\%$.

Columns 4-5 show students' choice of STEM major is positively affected by trade exposure if they presumably first attended college during 2000-2010 and 2000-2007.

Comparing Tables 2.3-2.5 I find that results are consistent across the two different datasets. For example, import competition has an overall positive effect on students' choice of STEM major. Males are more impacted by trade exposure than females regarding choice of STEM major as the estimates for female subsamples are not significant from either dataset. Moreover, the magnitudes of estimates in Table 2.5 are close to its counterparts in Tables 2.3 and 2.4.

Table 2.6: 2SLS Estimates by Field

	Business	Health professions	Social sciences	Education	Humanities	Others
	(1)	(2)	(3)	(4)	(5)	(6)
A. Underclassmen - NLSY97						
(Imports from *low income* to U.S.)/worker	0.0135	−0.0222	−0.0433*	−0.0053	0.0003	−0.028
	(0.033)	(0.033)	(0.024)	(0.022)	(0.032)	(0.037)
B. Upperclassmen - NLSY97						
(Imports from *low income* to U.S.)/worker	0.0038	−0.0345*	−0.0003	0.0057	−0.0269	−0.0063
	(0.024)	(0.018)	(0.012)	(0.017)	(0.024)	(0.033)
C. ACS						
(Imports from *low income* to U.S.)/worker	−0.0527**	−0.0340*	0.0050	−0.0191	0.0010	−0.0079
	(0.021)	(0.018)	(0.019)	(0.018)	(0.021)	(0.020)

Notes: Panels A and B use NLSY97 and focus on choice of major for college underclassmen and upperclassmen, respectively. The choice of major in the first part of college is included as a control in panel B. Standard errors in parentheses are robust to heteroskedasticity and clustered on the c-zone for specifications in panels A and B. C-zone linear time trend, c-zone 1997 fixed effect, and cohort fixed effects are included in each column of panels A and B. State linear time trend and state of birth fixed effect are included in each column of panel C. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

The results in the previous tables present that students are positively affected by trade exposure regarding the choice of STEM major. However, an increase in the probability of choosing STEM majors might lead to fewer students selecting other fields. I therefore substitute the binary variables of other fields (business, health professions, social sciences, education, humanities, and others) for the dependent variable STEM_{ist} in equation 2.9 to explore whether students are less likely to choose non-STEM majors due to import competition. Panel A of Table 2.6 suggests that college underclassmen are less likely to major in social sciences, while I do not observe any statistically significant effect on college underclassmen's choice of other fields. For college upperclassmen's choice of major, panel B shows trade exposure has a negative effect on the choice of health professions, while no significant results can be found in other fields. In addition to NLSY97, I also include the results from ACS data in panel C. The estimates in panel C suggest that import competition faced by STEM occupations reduces the probability of majoring in business and health professions. In Table 2.6, I find that only the field of health professions suggests more consistent results across the two different datasets. For the fields of education and humanities, their insignificant estimates across panels in the table imply that education and humanities are the least affected fields by import competition specific to STEM occupations.

Table 2.7: Migration

	Non-migrants	
	States (1)	C-zones (2)
A. Underclassmen		
(Imports from *low income* to U.S.)/worker (IMP)	0.0965**	0.0792
	(0.041)	(0.059)
Estimated effects (pp)	1.19	0.98
Number of observations	5,128	4,880
B. Upperclassmen		
(Imports from *low income* to U.S.)/worker (IMP)	0.0488**	0.0589**
	(0.020)	(0.026)
Estimated effects (pp)	0.60	0.73
Number of observations	5,128	4,880

Notes: Panels A and B use NLSY97 and focus on choice of major for underclassmen and upperclassmen, respectively. The choice of major in the first part of college is included as a control in panel B. Standard errors in parentheses are robust to heteroskedasticity and clustered on the c-zone for specifications in panels A and B. C-zone linear time trend, c-zone 1997 fixed effect, and cohort fixed effects are included in each column of panels A and B. State linear time trend and state of birth fixed effect are included in each column of panel C. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Another aspect I would like to explore is the migration pattern in my sample. So far I have not differentiated between people who did or did not migrate when they first attended college. However, people who migrated to pursue college education might be intrinsically different from those who did not. The differences, for example, might lie in their family backgrounds or personalities. In addition, my results so far have only accounted for the local impact of pre-college trade exposure on students' choice of STEM major, which means I only focus on import competition faced by pre-college local labor markets. Nevertheless, the environment and the location of a college might also play a vital role in students' choice of college major. Of the 5495 people in my sample, 367 of them (or 6.7%) migrated to other states for attending college. Besides state-to-state migration, I also look at migration between c-zones. There were 614 of them (or 11.2%) migrating to other c-zones for college attendance.[36] These migration rates are consistent with existing literature on historical migration pattern. For example, Molloy et al. (2011) find that cross-state and cross-commuting zone migration rates were 8.9% and 12.9% in 2000, respectively. Table 2.7 shows the results when I restrict my sample to those who stayed in the same states or c-zones while first attending college. Column 1 of panel A shows that trade exposure still positively impacts college underclassmen's choice of STEM major when I restrict the sample to those who stayed in the same states. However, for those who stayed in the same c-zones, the estimate in column 2 of panel A remains positive, but not significant. Columns 1 and 2 of panel B instead suggest import competition has a significant positive effect on college upperclassmen's choice of STEM major for both types of non-migrants. From Table 2.7, I find that significance levels and the magnitudes of coefficients do not have a noticeable change compared to previous results, thus providing evidence that my outcomes are not driven by unobserved differences between migrants and non-migrants or by unobserved characteristics of college locations.

While my results hold firmly in different specifications and by using different datasets, the results could still be driven by unobserved factors that are behind increased trade exposure and students' choice of STEM major. To verify that my results correctly capture the causal relationship between the measure of trade exposure and STEM major choice rather than the secular trend due to unobservables, I regress students' choice of STEM major on future imports from low-income countries.[37] Table 2.8 reports the results of the falsification exercise in panels A and B by using the

[36] I find that migration is more common for students right after graduation. 15% and 25.5% of the NLSY97 sample, respectively, migrated to other states and c-zones after college graduation.

[37] I use post-graduation imports as future imports. For example, if a student graduates from a 4-year college in 2010, then I use the average of 2015 and 2016 imports as my future imports.

Table 2.8: Falsification Exercise

	Under (1)	Upper (2)
A. NLSY97		
(Future imports from *low income* to U.S.)/worker	0.03	−0.0016
	(0.023)	(0.017)
Number of observations	5,308	5,308
B. ACS		
(Future imports from *low income* to U.S.)/worker		-0.0400^{***}
		(0.015)
Number of observations		403,902

Notes: "Under" and "Upper" refer to choices of major for college underclassmen and upperclassmen. Standard errors are robust to heteroskedasticity and clustered on the c-zone in each column of panel A. Standard errors in parentheses are robust to heteroskedasticity and clustered on state of birth for specifications in panel B. State linear time trend and state of birth fixed effect are included in each column of panel B. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

NLSY97 and ACS data, respectively. If the estimated coefficients on future imports are significant and positive, then the results in previous tables might be driven by the secular trend. However, the insignificant estimates in columns 1 and 2 of panel A suggest that my results from the NLSY97 in previous tables cannot be driven by the secular trend due to unobservables. While the estimate in column 2 of panel B is significant at the 1% level, its sign is negative. This result implies the causal relationship derived from ACS does not come from the secular trend either.

While my measure of trade exposure focuses on imports from low-income countries, I also calculate import competition from countries of different income levels to explore their differential impacts on major choice. Exporting countries are classified into three income levels based on their gross national income (GNI) per capita in 2000: low, middle, and high.[38] Panel A of Table 2.9 shows the results by using NLSY97. The estimates in columns 1 and 4 of panel A are from Table

[38]I combine low-income and lower-middle-income countries together and classify them as the low-income group according to their gross national income (GNI) per capita in 2000: a country belongs to the low-income group if its GNI per capita in 2000 was below $755; a country belongs to the lower-middle-income group if its GNI per capita in 2000 was between $755 and $2994; a country belongs to the upper-middle-income group if its GNI per capita in 2000 was between $2995 and $9265; a country belongs to the high-income group if its GNI per capita in 2000 was over $9265.

Table 2.9: 2SLS Estimates by Income level of Exporting Countries

	Underclassmen			Upperclassmen		
	Income levels					
	Low (1)	Middle (2)	High (3)	Low (4)	Middle (5)	High (6)
A. NLSY97						
(Imports to U.S.)/worker	0.085**	0.1421	0.0333*	0.0585***	0.2042**	0.0162*
	(0.035)	(0.119)	(0.018)	(0.020)	(0.095)	(0.010)
Number of observations	5,495	5,495	5,495	5,495	5,495	5,495
B. ACS						
(Imports to U.S.)/worker				0.0598***	0.0546	0.0164*
				(0.023)	(0.034)	(0.009)
Number of observations				431,428	431,428	431,428

Notes: The choice of major in the first part of college is included as a control in the specifications of columns 4-6. Standard errors in parentheses are robust to heteroskedasticity and clustered on the c-zone in each column of panel A. C-zone linear time trend, c-zone 1997 fixed effect, and cohort fixed effects are included in each column of panel A. Standard errors in parentheses are robust to heteroskedasticity and clustered on state of birth for specifications in panel B. State linear time trend and state of birth fixed effect are included in each column of panel B. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

2.2, which are the baseline results and show the impact from low-income countries. Columns 2 suggests that there is no significant relationship between college underclassmen's choice of STEM major and import competition from middle-income countries. The estimate in column 3 shows that the impact from high-income countries has a positive effect on college underclassmen' choice of STEM major. Columns 5 and 6, however, indicate that import competition from middle- and high-income countries has a positive effect on college upperclassmen's choice of STEM major. The estimates 0.2042 and 0.0162 are significant at the 5% and 10% levels, respectively. Comparing the magnitudes of the estimates in columns 4-6, I find middle-income countries have a surprisingly large effect on college upperclassmen' choice, and that the impact of high-income countries is trivially small.

Panel B of Table 2.9 presents the estimates by using ACS data. Since people reported their final bachelor's degrees instead of initial choices of major to ACS, the estimates from ACS data are placed in columns 4-6 to compare the results of upperclassmen's choice of major from NLSY97. The result in column 4 is from the baseline estimate in column 1 of Table 2.5. Column 5 suggests that increased imports from middle-income countries does not have a significant effect on students' choice of STEM major. Column 6 indicates that import competition from high-income countries also increases the probability of majoring in STEM, but the magnitude of the effect is much smaller.

2.5.2 Labor Market Outcomes Using CPS

Subsection 2.5.1 has shown that increased trade exposure faced by STEM occupations has a positive and statistically significant effect on students' choice of STEM major. In this subsection, I use 1998-2010 CPS data to explore whether STEM occupations enjoyed an advantage over non-STEM jobs in terms of labor market outcomes when the U.S. experienced growing import competition from low-income countries from the late 1990s through the 2000s. Results in this subsection also help me determine the relationship between trade exposure ξ and the mean of the self-belief distribution μ_i^x in the theoretical model. I also use \$450 to represent the change in trade exposure during this time period (i.e., ΔIMP = \$450).

Table 2.10: Effects of Trade Exposure on Log Weekly Wages by Age - CPS

	Manufacturing sector			Non-manufacturing sector		
Dependent variable: log(wages)	23-64 (1)	23-40 (2)	41-64 (3)	23-64 (4)	23-40 (5)	41-64 (6)
(Imports from *low income* to U.S.)/worker (IMP)	-0.0656^{***}	-0.1040^{***}	-0.0457	-0.0944^{***}	-0.1178^{***}	-0.0864^{***}
	(0.024)	(0.035)	(0.035)	(0.017)	(0.024)	(0.024)
IMP $\times$ 1_{stem_occ}	0.0727^{***}	0.0469^{***}	0.0908^{***}	0.0440^{***}	0.0410^{***}	0.0454^{***}
	(0.011)	(0.017)	(0.017)	(0.010)	(0.014)	(0.012)
Est. effects - non-STEM (%)	-0.81	-1.29	-0.57	-1.17	-1.46	-1.07
Est. effects - STEM (%)	0.09	-0.71	0.56	-0.62	-0.95	-0.51
Number of observations	268,645	117,297	151,348	1,592,669	758,777	833,892

Notes: The dependent variable is log weekly wages in 2007 US\$. Respondents in the sample are divided into six age cohorts. The observations in the sample with the top and bottom 1% of weekly wages are dropped in case of bias from extreme values. Standard errors in parentheses are robust to heteroskedasticity and clustered on the state of work×cohort. State linear time trend, state of work, occupation, industry, and age cohort fixed effects are included in each column. All imports data are in 2007 US\$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Table 2.10 reports the effects of import competition on log weekly wages by using equation 2.11. Considering that import competition might have differential effects across sectors and on different age groups, I analyze the CPS data in two sectors (manufacturing and non-manufacturing) and divide the sample into younger (age 23-40) and older (age 41-64) cohorts.

Columns 1-3 of Table 2.10 show the estimates when I restrict the sample to the manufacturing sector. Column 1 suggests that import competition has a negative and statistically significant impact on the weekly wages of non-STEM occupations in the manufacturing sector. The estimate -0.0656 implies a reduction of weekly wages by 0.81%.[39] However, the impact of import competition for STEM jobs regarding weekly wages is trivially small as the estimates -0.0656 and 0.0727 almost cancel each other out. For the younger cohort in column 2, the estimates show that both STEM and non-STEM jobs are negatively affected in terms of weekly wages, but non-STEM occupations encounter a more serious negative impact than STEM jobs do. The estimates in column 2 suggest import competition decreases weekly wages by 1.29% and 0.71% for non-STEM and STEM jobs, respectively.[40] As for the older cohort in column 3, STEM occupations imply an even stronger advantage over non-STEM jobs regarding weekly wages since the estimated coefficient on $\text{IMP} \times 1_{stem\_occ}$ is positive and twice larger than the one on IMP (in absolute value).

The specifications in columns 4-6 of Table 2.10 use the non-manufacturing subsample. Column 4 suggests an overall negative effect of import competition on weekly wages for both STEM and non-STEM occupations in the non-manufacturing sector. The estimates in column 4 are associated with decreases in weekly wages by 1.17% and 0.62% for non-STEM and STEM occupations, respectively.[41] If we use the average weekly wage of $790 in non-manufacturing and assume that people work 52 weeks a year, then these decreases of weekly wages are also equivalent to drops of $481 and $255, respectively, for non-STEM and STEM occupations from the late 1900s through the 2000s.[42] For the younger cohort, column 5 similarly indicates that STEM jobs are less negatively influenced by import competition. As for people aged above 40, column 6 suggests the negative effect on weekly wages for STEM jobs (-0.51%) is half that for non-STEM occupations (-1.07%). Comparing the results across manufacturing and non-manufacturing, I find that the magnitudes of wage effects are generally larger for non-manufacturing than for manufacturing. As pointed out in

[39] $-0.0656 \times 0.45 \times 0.275 \approx -0.81\%$.

[40] $-0.1040 \times 0.45 \times 0.275 \approx -1.29\%$; $(-0.1040 + 0.0469) \times 0.45 \times 0.275 \approx -0.71\%$.

[41] $-0.0944 \times 0.45 \times 0.275 \approx -1.17\%$; $(-0.0944 + 0.044) \times 0.45 \times 0.275 \approx -0.62\%$.

[42] The average weekly wages of $790 in non-manufacturing is derived from CPS 1998-2010.

Autor, Dorn, and G. Hanson (2013), displaced workers from manufacturing lead to a rise in supply of labor in non-manufacturing, which causes stronger downward pressure on wages outside the manufacturing sector.

Based on the results in Table 2.10, the relative weekly wages of STEM occupations increase due to greater import competition from low-income countries in the late 1990s and the 2000s, as non-STEM occupations experience a steeper decline in their weekly wages. This outcome also implies an increase in the mean of people's self-belief distribution due to better relative wages for STEM majors in my theoretical model, which suggests weekly wages could be a channel through which increased trade exposure positively affects the probability of students choosing STEM majors.

Table 2.11: Effects of Trade Exposure on Log Weekly Wages by Age and Gender - CPS

	Manufacturing sector			Non-manufacturing sector		
Dependent variable:	23-64	23-40	41-64	23-64	23-40	41-64
log(wages)	(1)	(2)	(3)	(4)	(5)	(6)
A. Males						
(Imports from *low income* to U.S.)/worker (IMP)	−0.0536**	−0.0752**	−0.0512	−0.0968***	−0.1446***	−0.0732***
	(0.024)	(0.029)	(0.038)	(0.017)	(0.027)	(0.024)
IMP × 1_{stem_occ}	0.0819***	0.059***	0.0975***	0.0650***	0.0694***	0.0583***
	(0.013)	(0.022)	(0.017)	(0.012)	(0.019)	(0.014)
Est. effects - non-STEM (%)	−0.66	−0.93	−0.63	−1.20	−1.79	−0.91
Est. effects - STEM (%)	0.35	−0.20	0.57	−0.39	−0.93	−0.18
Number of observations	182,983	79,982	103,001	756,170	375,177	380,993
B. Females						
(Imports from *low income* to U.S.)/worker (IMP)	−0.0948**	−0.1795**	−0.0359	−0.0958***	−0.0999***	−0.0993***
	(0.039)	(0.072)	(0.045)	(0.020)	(0.025)	(0.029)
IMP × 1_{stem_occ}	0.0469**	0.0065	0.0877**	0.0134	0.0038	0.0259
	(0.022)	(0.025)	(0.037)	(0.015)	(0.021)	(0.017)
Est. effects - non-STEM (%)	−1.19	−2.22	−0.44	−1.17	−1.24	−1.23
Est. effects - STEM (%)	−0.59	−2.14	0.64	−1.02	−1.19	−0.91
Number of observations	85,662	37,315	48,347	836,498	383,600	452,898

Notes: The dependent variable is log weekly wages in 2007 US$. Respondents in the sample are divided into six age cohorts. The observations with the top and bottom 1% of weekly wages are dropped in case of bias from extreme values. Standard errors in parentheses are robust to heteroskedasticity and clustered on the state of work×cohort. State linear time trend, state of work, occupation, industry, and age cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Aside from dividing the sample into different age groups and sectors, I also explore whether trade exposure has differential effects on weekly wages across genders. Table 2.11 shows the results when the sample is split into male and female subsamples. When I restrict my sample to males as shown in panel A of Table 2.11, the results suggest that STEM occupations consistently have an advantage over non-STEM jobs in both sectors and across age groups. The estimates in columns 1 and 3 of panel A even imply import competition has a net positive effect on weekly wages for STEM jobs. Comparing the estimates between the two sectors in panel A, I also find import competition generally has a stronger negative effect on weekly wages in the non-manufacturing sector than in the manufacturing sector.

When I use the female subsample as shown in panel B of Table 2.11, the estimated coefficients on IMP are negative and mostly significant across the two sectors and age groups. This implies females in non-STEM occupations, like males, are negatively affected regarding weekly wages. However, the relative advantage of STEM occupations in the face of trade exposure is only observed in the manufacturing sector for females as shown by columns 1 and 3 in panel B. Comparing the estimates in columns 1-3 of across panels, I also find that the positive effect of being in STEM occupations is stronger for males than for females, which is implied by the larger positive coefficients on IMP $\times$ 1_{stem_occ} in panel A than in panel B.

Table 2.12: Effects of Trade Exposure on Employment Status by Age - CPS

	Manufacturing sector			Non-manufacturing sector		
Dependent variable: Unemployed	23-64 (1)	23-40 (2)	41-64 (3)	23-64 (4)	23-40 (5)	41-64 (6)
(Imports from *low income* to U.S.)/worker (IMP)	0.0425***	0.0523**	0.0348**	0.0340***	0.0345**	0.0349***
	(0.014)	(0.022)	(0.017)	(0.009)	(0.013)	(0.011)
IMP $\times$ 1_{stem_occ}	−0.0231***	−0.0278***	−0.0204***	−0.0138***	−0.0175***	−0.0116***
	(0.004)	(0.006)	(0.006)	(0.003)	(0.004)	(0.003)
Est. effects - non-STEM (pp)	0.53	0.65	0.43	0.42	0.43	0.43
Est. effects - STEM (pp)	0.24	0.30	0.18	0.25	0.21	0.29
Number of observations	1,202,809	514,591	688,218	7,826,842	3,575,150	4,251,692

Notes: The dependent variable is dichotomous and equal to 1 if respondents are unemployed. Respondents in the sample are divided into six age cohorts. Standard errors in parentheses are robust to heteroskedasticity and clustered on the state of work×cohort. State linear time trend, state of work, occupation, industry, and age cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Aside from weekly wages, I also explore whether respondents' employment status is influenced by trade exposure from low-income countries. Table 2.12 presents the results by using equation 2.11, where the dependent variable is dichotomous and equal to 1 if respondents are unemployed.

Columns 1-3 show the results when the sample is restricted to workers in the manufacturing sector. The estimates in column 1 imply that import competition increases the probability of unemployment for non-STEM occupations by 0.53 percentage points. Nevertheless, the probability of unemployment only rises by 0.24 percentage points for STEM jobs during the same period. For the younger and older cohorts in columns 2 and 3, I also observe that workers in STEM occupations are less likely to lose their jobs compared to non-STEM occupations as the coefficients on IMP $\times$ 1_{stem_occ} are negative and significant at the 1% level.

Columns 4-6 of Table 2.12 instead focus on the non-manufacturing sector. Column 4 suggests that import competition increases unemployment for workers in both STEM and non-STEM occupations. However, people in STEM jobs still enjoy an advantage and are more resistant to negative effects brought about by import competition, since non-STEM occupations face a much higher increase in the probability of unemployment due to trade shocks. For example, the estimates in column 4 are associated with rises in unemployment by 0.42 and 0.25 percentage points for non-STEM and STEM occupations, respectively. For the younger cohort in column 5, the increase in the probability of unemployment for non-STEM jobs (0.43 pp) is twice as much as the one for STEM (0.21 pp).

According to Table 2.12, the relative probability of unemployment for STEM jobs will decrease due to import competition. The relative advantage of STEM jobs regarding employment status also resonates with Autor, Dorn, and G. H. Hanson (2015) who similarly find that the employment of abstract-task-intensive occupations (e.g., managerial/professional/technical jobs) is least impacted by Chinese import exposure compared to manual-task-intensive and routine-task-intensive occupations. The results in Table 2.12 further imply a rise in the mean of the self-belief distribution regarding relative job stability as workers with STEM jobs are less likely to become unemployed, which again helps explain why import competition positively influences students' choice of STEM major.

Since the effects of trade exposure on employment status might differ across genders, Table 2.13 presents the relevant estimates by gender. Columns 1-3 of panel A show that import competition

Table 2.13: Effects of Trade Exposure on Employment Status by Age and Gender - CPS

	Manufacturing sector			Non-manufacturing sector		
Dependent variable:	23-64	23-40	41-64	23-64	23-40	41-64
Unemployed	(1)	(2)	(3)	(4)	(5)	(6)
A. Males						
(Imports from *low income* to U.S.)/worker (IMP)	0.0459***	0.0501**	0.0438**	0.0440***	0.0446**	0.0453***
	(0.014)	(0.022)	(0.019)	(0.012)	(0.019)	(0.015)
IMP $\times$ 1_{stem_occ}	−0.0237***	−0.0334***	−0.0172***	−0.0187***	−0.0217***	−0.0169***
	(0.005)	(0.006)	(0.006)	(0.003)	(0.004)	(0.004)
Est. effects - non-STEM (pp)	0.57	0.62	0.54	0.54	0.55	0.56
Est. effects - STEM (pp)	0.27	0.21	0.33	0.31	0.28	0.35
Number of observations	818,673	348,967	469,706	3,914,842	1,813,453	2,101,389
B. Females						
(Imports from *low income* to U.S.)/worker (IMP)	0.0350**	0.0534*	0.0175	0.0241***	0.0237***	0.0249***
	(0.015)	(0.028)	(0.017)	(0.006)	(0.009)	(0.008)
IMP $\times$ 1_{stem_occ}	−0.0198**	−0.0090	−0.0301***	−0.0077**	−0.0163***	−0.0020***
	(0.008)	(0.013)	(0.010)	(0.004)	(0.004)	(0.006)
Est. effects - non-STEM (pp)	0.22	0.66	0.43	0.30	0.29	0.31
Est. effects - STEM (pp)	0.19	0.55	−0.16	0.20	0.09	0.28
Number of observations	384,136	165,624	218,512	3,912,000	1,761,697	2,150,303

Notes: The dependent variable is dichotomous and equal to 1 if respondents are unemployed. Respondents in the sample are divided into six age cohorts. Standard errors in parentheses are robust to heteroskedasticity and clustered on the state of work×cohort. State linear time trend, state of work, occupation, industry, and age cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

leads to a significant increase in the probability of unemployment for males with STEM and non-STEM jobs in the manufacturing sector, but the negative impact is smaller for STEM occupations, because of the negative coefficients on IMP $\times$ 1_{stem_occ}. Females in the manufacturing sector, however, are less negatively affected regarding employment status as suggested by column 1 of panel B. For non-STEM jobs in the manufacturing sector, the probability of unemployment rises by 0.57 percentage points for males, but only increases by 0.22 percentage points for females.

When I use the subsample of the non-manufacturing sector, columns 4-6 of panel A again show that import competition has an overall negative impact on employment status for males in both STEM and non-STEM occupations, but imposes a weaker effect on STEM jobs. When I compare the estimates in columns 4-6 across panels A and B, I find that import competition has a much weaker effect for females. For instance, column 4 suggests that the probability of unemployment increases by 0.54 and 0.31 percentage points for males in non-STEM and STEM jobs, respectively.

Nevertheless, the probability only rises by 0.3 and 0.2 percentage points for females in non-STEM and STEM jobs, respectively. Moreover, I find that the relative advantage of working in STEM occupations is stronger for males than for females as indicated by the magnitudes of the coefficients on IMP $\times$ 1_{stem_occ} in columns 4-6.

Table 2.14: Effects of Trade Exposure on Full-/Part-Time Employment by Age - CPS

	Manufacturing sector			Non-manufacturing sector		
Dependent variable:	23-64	23-40	41-64	23-64	23-40	41-64
Full-time	(1)	(2)	(3)	(4)	(5)	(6)
(Imports from *low income* to U.S.)/worker (IMP)	-0.0461^{***}	-0.0512^{***}	-0.0400^{***}	-0.0302^{***}	-0.0327^{**}	-0.0245^{**}
	(0.009)	(0.013)	(0.013)	(0.009)	(0.013)	(0.010)
IMP $\times$ 1_{stem_occ}	0.0222^{***}	0.0184^{***}	0.0251^{***}	0.0194^{***}	0.0229^{***}	0.0175^{***}
	(0.003)	(0.006)	(0.004)	(0.004)	(0.006)	(0.005)
Est. effects - non-STEM (pp)	-0.57	-0.63	-0.50	-0.37	-0.40	-0.30
Est. effects - STEM (pp)	-0.30	-0.41	-0.18	-0.13	-0.12	-0.09
Number of observations	1,141,301	486,242	655,059	7,488,349	3,392,340	4,096,009

Notes: The dependent variable is dichotomous and equal to 1 if respondents are full-time employed. Respondents in the sample are divided into six age cohorts. Standard errors in parentheses are robust to heteroskedasticity and clustered on the state of work×cohort. State linear time trend, state of work, occupation, industry, and age cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

In addition to the analysis of employment status, I also use equation 2.11 with the dichotomous dependent variable Full-time$_{i,t}$ to explore whether trade exposure affects full-/part-time employment. Since full-time jobs usually provide a more stable and secure career path compared to part-time jobs, I view full-time employment as one type of job stability indices. Column 1 shows that import competition leads to a significant decrease in the probability of full-time employment by 0.57 and 0.3 percentage points for non-STEM and STEM occupations in the manufacturing sector, respectively. Since the part-time employment rate is 4.64% in manufacturing during the early 2000s, this also implies the probability of working part-time rises by 12.3% and 6.5%, respectively, for non-STEM and STEM occupations.[43] The result suggests the full-time employment of non-STEM occupations is more negatively impacted due to trade exposure. Columns 2 and 3 also show similar patterns for the younger and older cohorts.

[43] 0.57%/4.64% $\approx$ 12.3%; 0.3%/4.64% $\approx$ 6.5%.

When the sample is restricted to the non-manufacturing sector, the negative impact of import competition on full-time employment still exists. For example, the coefficient on IMP in column 4 is associated with a 0.37 percentage point decrease in the probability of full-time employment for non-STEM jobs, which it is equivalent to a 2.52% increase in the rate of part-time employment.[44] The probability for STEM jobs instead drops by 0.13 percentage points, which is equivalent to a 0.88% decrease in the rate of part-time employment.[45] The younger and older cohorts in columns 5 and 6 also show the negative effect of import competition and the relative advantage of STEM occupations in the face of import competition. Comparing the results across the two sectors, I find that import competition has a stronger negative effect on full-time employment in manufacturing than in non-manufacturing.

The results in Table 2.14 suggest that the relative probability of full-time employment for STEM jobs will increase due to greater import exposure as STEM occupations are more likely to work full-time. This also means that the mean of people's self-belief distribution regarding relative job stability increases as the probability of full-time employment for non-STEM occupations decreases more than STEM jobs do.

Table 2.15 shows the effects of import competition on full-time employment across genders. As suggested by panel A of Table 2.15, males with either non-STEM or STEM jobs are negatively impacted regarding full-time employment in both the manufacturing and non-manufacturing sectors. STEM occupations, however, still enjoy an advantage over non-STEM jobs in the face of import competition as the coefficients on $\text{IMP} \times 1_{stem\_occ}$ are positive across columns and thus weaken the negative effects of import competition.

When I restrict the sample to females, column 1 of panel B suggests that there is a negative and significant relationship between import competition and the probability of full-time employment for females in manufacturing. The estimates in column 1 of panel B are associated with decreases in the probability of full-time employment by 0.61 and 0.22 percentage points for non-STEM and

[44] The part-time employment rate is 14.7% for the non-manufacturing sector in the early 2000s. $0.37\%/14.7\% \approx 2.52\%$.

[45] $0.13\%/14.7\% \approx 0.88\%$.

Table 2.15: Effects of Trade Exposure on Full-/Part-Time Employment by Age and Gender - CPS

	Manufacturing sector			Non-manufacturing sector		
Dependent variable:	23-64	23-40	41-64	23-64	23-40	41-64
Full-time	(1)	(2)	(3)	(4)	(5)	(6)
A. Males						
(Imports from *low income* to U.S.)/worker (IMP)	−0.0448***	−0.0522***	−0.0395***	−0.0338***	−0.0456**	−0.0286**
	(0.009)	(0.010)	(0.014)	(0.011)	(0.019)	(0.012)
IMP × 1_{stem_occ}	0.0203***	0.0192***	0.0209***	0.0238***	0.0331***	0.0158***
	(0.003)	(0.006)	(0.003)	(0.004)	(0.007)	(0.004)
Est. effects - non-STEM (pp)	−0.55	−0.65	−0.49	−0.42	−0.56	−0.35
Est. effects - STEM (pp)	−0.30	−0.41	−0.23	−0.12	−0.15	−0.16
Number of observations	780,681	331,525	449,156	3,735,672	1,717,473	2,018,199
B. Females						
(Imports from *low income* to U.S.)/worker (IMP)	−0.0489***	−0.0512	−0.0369	−0.0289***	−0.0229**	−0.0235**
	(0.018)	(0.031)	(0.023)	(0.010)	(0.011)	(0.011)
IMP × 1_{stem_occ}	0.0308***	0.0135	0.0451***	0.0175**	0.0151	0.0211**
	(0.009)	(0.014)	(0.013)	(0.008)	(0.011)	(0.010)
Est. effects - non-STEM (pp)	−0.61	−0.63	−0.46	−0.36	−0.28	−0.29
Est. effects - STEM (pp)	−0.22	−0.47	0.10	−0.14	−0.10	−0.03
Number of observations	360,620	154,717	205,903	3,752,677	1,674,867	2,077,810

Notes: The dependent variable is dichotomous and equal to 1 if respondents are unemployed. Respondents in the sample are divided into six age cohorts. Standard errors in parentheses are robust to heteroskedasticity and clustered on the state of work×cohort. State linear time trend, state of work, occupation, industry, and age cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

STEM jobs, respectively. Nevertheless, the estimates in columns 2 and 3 of panel B show that full-time employment has no significant relationship with import competition for females in non-STEM occupations when the sample is split into younger and older cohorts, and that the relative advantage of STEM occupations is observed for females in the older, but not in the younger cohort. For females in the non-manufacturing sector, columns 4-6 suggest the full-time employment status of non-STEM jobs consistently faces negative effects from import competition, and that the younger cohort does not benefit from working in STEM occupations.

2.5.3 Labor Market Outcomes Using NLSY97

Subsection 2.5.2 uses CPS data to provide empirical evidence that STEM occupations are more resistant to the negative impact on the labor market outcomes brought by increased import competition. The channels through which trade exposure affects students' choice of STEM major are therefore established. In this subsection I use NLSY97 to analyze the relative performance of STEM majors in the labor market compared to non-STEM fields.

Table 2.16: Effects of Trade Exposure on Wages by Gender - NLSY97

	Over 30 weeks			Full sample		
Dependent variable:	All	Males	Females	All	Males	Females
log(wages)	(1)	(2)	(3)	(4)	(5)	(6)
A. STEM switchers						
(Imports from *low income* to U.S.)/worker (IMP)	−0.0055	−0.0561**	0.0255	−0.0045	−0.0540**	0.0240
	(0.017)	(0.023)	(0.031)	(0.017)	(0.025)	(0.029)
IMP × 1_{stem}	0.0429	0.1170	−0.0607	0.0005	0.0561	−0.0904*
	(0.042)	(0.071)	(0.046)	(0.045)	(0.083)	(0.047)
Number of observations	22,082	9,153	12,929	23,933	9,889	14,044
B. STEM non-switchers						
(Imports from *low income* to U.S.)/worker (IMP)	−0.0102	−0.0590***	0.0200	−0.0087	−0.0628***	0.0234
	(0.014)	(0.019)	(0.028)	(0.014)	(0.022)	(0.028)
IMP × 1_{stem}	0.0154	0.0355**	0.0269	0.0270	0.0545**	0.0486
	(0.017)	(0.018)	(0.044)	(0.021)	(0.022)	(0.043)
Number of observations	24,048	10,829	13,219	26,041	11,679	14,362

Notes: The dependent variable is log weekly wages in 2007 US$. Standard errors in parentheses are robust to heteroskedasticity and clustered on the c-zone. The c-zone linear time trend, c-zone 1997 fixed effect, occupation, industry, and cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Table 2.16 reports the effects of trade exposure on log weekly wages by using equation 2.12. Here, I classify students who chose STEM majors into two groups: STEM switchers and STEM non-switchers. STEM switchers refer to those who selected STEM majors in either the first or second part of college but not both, while STEM non-switchers are students who chose STEM majors in both parts of college.

In panel A the indicator variable 1_{stem} equals one if respondents are STEM switchers, and the sample excludes STEM non-switchers. The sample in columns 1-3 of panel A is restricted to those who work over 30 weeks in one year. The estimates in columns 1 and 3 of panel A indicate that import competition does not have a significant effect on weekly wages for the pooled and the female samples. However, the significant estimates in column 2 of panel A suggest that trade exposure negatively affects the weekly wages for males in non-STEM majors, while STEM switchers do not exhibit any advantage in the face of import competition as the coefficient on the interaction term is insignificant. When I use the full sample in columns 4-6 of panel A, males in non-STEM majors and male non-switchers are similarly negatively affected regarding weekly wages. The significant coefficient on the interaction term in column 6, however, suggests that female STEM switchers are even more negatively affected by import competition than females in non-STEM majors.

In panel B of Table 2.16 the indicator variable 1_{stem} equals one if respondents are STEM non-switchers, and the sample excludes STEM switchers. Columns 1-3 of panel B use the sample restricted to those who work at least 30 weeks in a single year. The estimates in column 2 of panel B show trade exposure has a negative and statistically significant effect on the weekly wages for males in non-STEM majors, and that STEM majors show a clear advantage as the estimated coefficient on IMP $\times$ 1_{stem} is statistically significant and positive. When I use the full sample in columns 4-6 of panel B, the estimates in column 5 are statistically significant and suggest that weekly wages of males in STEM majors are more resistant to the negative impact brought by import competition.

In the appendix, fig. B.8 plots the percent difference of weekly wages between STEM and non-STEM occupations by using NLSY97. The horizontal axis is potential experience. To explore the heterogeneity of wage differential by level of import competition, I assign people to either “high" or “low" import competition according to the level of import competition faced by their c-zones. The figure shows that the weekly wages of STEM jobs are pronouncedly higher than non-STEM occupations by at least 30% across different years of potential experience. Moreover, the wage differential is much larger for people with less than 6 years of potential experience in high import competition c-zones compared to its counterpart in low import competition c-zones. The larger wage differential for people in high import competition areas also implies that STEM occupations enjoy higher relative wages in places more exposed to import shocks, which provides students with a stronger incentive to choose STEM majors. However, the higher wage differential in high import competition areas gradually subsides as people’s potential experience increases.

Aside from the exploration of weekly wages, I also use equation 2.12 to analyze the effect of import competition on employment status. The dependent variable in Table 2.17 is Unemployed$_{isjkt}$, which is dichotomous and equal to one if individual i was unemployed in year t. The indicator

Table 2.17: Effects of Trade Exposure on Employment Status by Gender - NLSY97

Dependent variable: Unemployed	All (1)	Males (2)	Females (3)
A. STEM switchers			
(Imports from *low income* to US)/worker (IMP)	0.0024	0.0284*	−0.0161
	(0.011)	(0.016)	(0.016)
IMP × 1_{stem}	−0.0034	0.0034	0.0075
	(0.018)	(0.031)	(0.024)
Number of observations	30,111	12,459	17,652
B. STEM non-switchers			
(Imports from *low income* to US)/worker (IMP)	0.0083	0.0343**	−0.0129
	(0.011)	(0.016)	(0.017)
IMP × 1_{stem}	−0.0080	−0.0195**	0.0003
	(0.007)	(0.009)	(0.020)
Number of observations	32,621	14,615	18,006

Notes: The dependent variable is dichotomous and equal to 1 if respondents are unemployed. Standard errors in parentheses are robust to heteroskedasticity and clustered on the c-zone. The c-zone linear time trend, c-zone 1997 fixed effect, occupation, industry, and cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

variable 1_{stem} in panel A equals one if respondents are STEM switchers. Columns 1 and 3 of panel A show that import competition has no significant influence on employment status when the pooled and female samples are used. Nevertheless, column 2 of panel A suggests that increased trade exposure leads to a significant rise in the probability of unemployment for all males as the estimated coefficient on IMP × 1_{stem} is not statistically significant. In panel B of Table 2.17 the indicator variable 1_{stem} represents STEM non-switchers. In column 2 of panel B, the positive sign of the estimated coefficient on IMP implies there is an increase in unemployment for males in non-STEM majors, while the negative sign of the estimated coefficient on IMP × 1_{stem} suggests that the negative impact is alleviated for males in STEM majors.

Comparing the results of Tables 2.16 and 2.17, I find that STEM non-switchers are more resistant to the negative impact brought by increase trade exposure than STEM switchers. One potential explanation for the finding is the difference in their career paths. For example, my sample suggests that only 8.2% of STEM switchers work in STEM occupations, while the proportion for STEM non-switchers in STEM jobs is 24.6%. Since STEM occupations can better shield people from the negative impacts of import competition as shown by section 2.5.2, STEM non-switchers are expected to have better performance in the face of rising import exposure.

2.6 Conclusions

This paper examines the relationship between trade exposure from low-income countries and the choice of STEM major in the U.S. Based on the works of Zafar (2011), Altonji et al. (2012), and Wiswall and Zafar (2015), I build a simple theoretical model to explain how trade exposure enters individuals' utility functions when students make their decisions on college majors. The implication of the model is that trade exposure influences people's utility through its effects on individuals' beliefs about labor market outcomes given their chosen majors.

I first construct an occupation-specific measure of trade exposure and use NLSY97 to explore the effect of import competition on choice of STEM major. I find that trade exposure has a significant positive effect on the choice of STEM major. The associated effects are 1.05 and 0.72 percentage point increases in the probability of choosing STEM majors in the first and second parts of college. However, I only observe the positive effect on choice of STEM major for males, but not for females when I split the sample into the male and female subsamples. For a robustness check of my results, I also use ACS to analyze the impact of trade exposure on choice of STEM major. The results from ACS consistently show that import competition increases students' probability of choosing STEM majors.[46]

To empirically test my model, I use CPS data to explore relative labor market outcomes of STEM occupations compared to non-STEM jobs. While trade exposure has an overall negative impact on the local labor market outcomes (weekly wages, employment status, and full-/part-time employment) from the late 1990s through the 2000s, STEM occupations are less negatively affected than non-STEM occupations. The relative advantage enjoyed by STEM occupations helps explain why trade exposure positively influences the probability of students choosing STEM majors. In addition, I also use NLSY97 to explore respondents' post-college performance in the labor market.

[46] In the appendix section, I further split STEM into two categories: engineering and non-engineering majors. Table B.6 shows the impact of trad exposure on the two categories, respectively.

I find that males who chose STEM fields in the first and second parts of college are less negatively impacted by trade exposure in terms of weekly wages and employment status. However, I do not observe similar results when I use the female subsample.

CHAPTER 3

THE EFFECT OF IMPORT EXPOSURE ON EDUCATION–OCCUPATION MISMATCH: A SUPPLY-DEMAND ANALYSIS

3.1 Introduction

The concept of education-job mismatch has been extensively explored in economics, because people with mismatched jobs tend to suffer from wage penalties (Robst 2007a; Malamud 2010; Nordin et al. 2010; Béduwé and Giret 2011; Bender and Roche 2013), a higher risk of unemployment (Wolbers 2003; Somers et al. 2019), or a lower level of job satisfaction (Malamud 2010; Béduwé and Giret 2011; Bender and Roche 2013; Zhu 2014; Shevchuk et al. 2015). Economists generally classify education-job mismatch into two categories: horizontal and vertical mismatches. Vertical mismatch refers to people with an educational level higher/lower than required by their jobs. This type of mismatch has been well documented in the literature (Heijke et al. 2003; Verhaest and Omey 2006; McGuinness 2006; McGuinness and Bennett 2007; Kupets 2016). Horizontal mismatch, on the other hand, refers to people working in an occupation that does not match their fields of education. For example, a magazine editor who has a college degree in math would be considered a horizontal mismatch. In this paper, I focus on horizontal mismatches.

According to the literature, the reasons for horizontal mismatch are generally classified into demand-related and supply-related factors (Robst 2007b; Nordin et al. 2010). Insufficient jobs in a certain field are considered as a demand-related factor, while promotion opportunities, work environment, and preferences are viewed as supply-related factors. This research also approaches horizontal mismatch from a supply-demand point of view. However, instead of looking at individual-level factors as mentioned above, this paper explores whether import exposure leads to an unbalanced market demand for and supply of college graduates and the resultant education-job mismatch.

Before diving into empirical approaches, I use the concept of a matching function to link the probability of mismatch with the supply of and demand for college graduates. The implication of the matching function in this paper is intuitive and simple: the probability of education-job match only depends on the number of unemployed workers from a degree field (supply) and the number of job vacancies matched with this field (demand). In the section of empirical approach, I first build a measure of import exposure by referring to the methods in Autor, Dorn, and G. Hanson (2013) and Acemoglu et al. (2016). By using the concept of an input-output table, the measure accounts for not only direct trade shocks experienced by industries, but also indirect ones faced by their output buyers and input suppliers. Moreover, the measure captures the level of import exposure faced by both manufacturing and non-manufacturing sectors.

I then use American Community Survey (ACS) 2011-2019 to investigate the effects of import exposure on education-job mismatch from 2011 through 2019. I find that overall it significantly increases due to trade shocks. A \$1,000 per person increase in import exposure predicts a rise in the probability of mismatch by 2.1 percentage points. When I divide my sample into female and male subsamples, the associated effects exhibit increases in the probability of mismatch by 2.4 and 1.6 percentage points, respectively, for males and females. In addition, I classify college majors into 16 degree fields to explore if import exposure has differential impacts across fields of education. My results show that engineering, math and statistics, psychology, and social sciences are more negatively impacted by increased import exposure regarding education-job match.

After I note the existence of a causal relationship between education-job mismatch and import exposure, the next step is to explore what drives import exposure to negatively affect education-job match. By approaching the problem from a supply-demand perspective. I examine import exposure's effects on the demand for and supply of college graduates. I treat the number of bachelor's degrees awarded and the employment of occupations matched with each degree fields as proxies for the supply and demand. For the supply side, I find that a \$1,000 per person rise in import exposure predicts an increase in the number of bachelor's degrees awarded in a 4-year college by 8.3%. Furthermore, the numbers of college degrees awarded to both male and female students also significantly increase respectively by 7.1% and 7.9%. Twelve out of 16 degree fields also exhibit significant increases in the numbers of degrees awarded. As for the demand side, import exposure, however, does not show pronounced effects on occupational employment for most fields of education.

According to my empirical results, there is a strong increase in the number of bachelor's degrees awarded due to trade shocks, but most occupational employment matched with each field of education does not exhibit a corresponding increase to absorb the surge of college graduates. Therefore, the unbalanced supply of and demand for college graduates might lead to a rise in the probability of education-job mismatch.

The rest of this chapter is organized as follows. Section 3.2 presents the matching function. Section 3.3 discusses the data. Section 3.4 shows the empirical approaches. Section 3.5 offers the empirical results. Section 3.6 concludes.

3.2 Theoretical Framework

This section uses the concept of a matching function to explain how education-occupation mismatch is connected with import exposure and to explore the driving forces behind mismatch. The idea of the matching function has been widely used in the field of macroeconomics, because of its tractability in empirical studies (Petrongolo and Pissarides 2001). A simple Cobb-Douglas matching function with constant returns to scale can be written as

$$m = \mu U^{\sigma} V^{1-\sigma}, \tag{3.1}$$

where m, U, and V are the numbers of new matches, unemployed workers, and job vacancies, respectively. Here, μ in equation 3.1 represents matching efficiency. For the purpose of this study, I maintain the structure of the Cobb-Douglas matching function, but define the variables differently as shown by equation 3.2.

$$m_j = \mu_j U_j^{\sigma} V_j^{1-\sigma}. \tag{3.2}$$

m_j denotes the number of matches for unemployed people with a degree in college major j, while μ_j still stands for matching efficiency, but now changes across college majors. This implies different fields of education do not face the same matching efficiency. For example, college graduates of a certain field might match with job vacancies more easily than others due to lower hiring standards. U_j represents the number of unemployed people with a degree in college major j. V_j is job vacancies for occupations that match college major j. For instance, if j is an engineering major, then V_j only includes vacancies for engineering-related occupations. The definition of job vacancies V in equation 3.2 differs significantly from the one in equation 3.1 as job vacancies in a standard matching function encompass all vacant jobs. Dividing both sides of equation 3.2 by U_j, the equation can then be expressed as:

$$p\left(\mu_j, \theta_j\right) = \frac{m_j}{U_j} = \mu_j \theta_j^{1-\sigma}, \tag{3.3}$$

with $\theta_j = \frac{V_j}{U_j}$ the labor tightness. The ratio of m_j to U_j can be interpreted as the probability of unemployed workers with a degree in j matched with field-specific vacant jobs, and I denote the probability by $p\left(\mu_j, \theta_j\right)$. Equation 3.3 shows that the probability of education-job match increases if labor tightness θ_j goes up. To explore how import exposure affects the probability, I assume that both V_j and U_j are functions of import exposure ξ.

$$\frac{\partial p\left(\mu_j, \theta_j\right)}{\partial \xi} = \mu_j \left(1-\sigma\right) \left(\frac{V_j}{U_j}\right)^{-\sigma} \left(\frac{U_j V_j^{'} - U_j^{'} V_j}{U_j^2}\right). \tag{3.4}$$

Equation 3.4 shows the differentiation of $p\left(\mu_j, \theta_j\right)$ with respect to ξ and suggests that the sign of $\frac{\partial p\left(\mu_j, \theta_j\right)}{\partial \xi}$ only depends on the numerator in the last parentheses. If $V_j^{'} > 0$ and $U_j^{'} < 0$, then $\frac{\partial p\left(\mu_j, \theta_j\right)}{\partial \xi} > 0$. This implies that import exposure increases the probability of education-job match due to a rise in demand (more vacancies) and a drop in supply (fewer unemployed workers). On the other hand, if $V_j^{'} < 0$ and $U_j^{'} > 0$, then $\frac{\partial p\left(\mu_j, \theta_j\right)}{\partial \xi} < 0$, which suggests import exposure increases the probability of education-job mismatch, because of a drop in demand (less vacancies) and an increase in supply (more unemployed workers). However, when $V_j^{'}$ and $U_j^{'}$ share the same sign, the sign of $\frac{\partial p(\mu_j,\theta_j)}{\partial \xi}$ becomes uncertain and relies on the relative magnitudes of V_j and U_j.

3.3 Data

I use American Community Survey (ACS) 2011-2019 to investigate the influence of import exposure on education-occupation mismatch. ACS has asked respondents with a bachelor's degree or above to report their field of bachelor's degree since 2009. In addition, ACS also collects information on respondents' primary occupations, industries, and related labor market outcomes such as wages and employment status. My sample is restricted to U.S.-born people who were aged 23-65 and not attending school at the time of survey. Moreover, since ACS does not have information on the fields of graduate degrees, respondents with an advanced degree (master's or doctoral degree) are not included in the sample to avoid overestimation of education-job mismatch as people tend to work in occupations related to their highest degrees.

To analyze the supply of college graduates across fields of study, I use institutional-level survey data from the Integrated Postsecondary Education Data System (IPEDS) at the National Center for Education Statistics (NCES). The IPEDS data provide detailed information on U.S. post-secondary institutions such as admissions, enrollment, degrees awarded, graduation rates, etc. To be consistent with the sample from ACS, I only include four-year colleges in IPEDS data for analysis and restrict the sample period to 2011-2019. There are roughly 2300-2600 four-year colleges participating in IPEDS surveys each year.[1]

Table 3.1 shows the proportions of mismatch for males and females across 16 fields of education. In this paper, I use an objective measure of education-job mismatch. Each field of education and their matched occupations are listed in Table C.1. People are considered to have mismatched occupations if their degree fields do not match their current occupations according to Table C.1.[2]

[1]The completion of IPEDS surveys is required for institutions that participate in or are applicants for participation in any federal student financial aid program. For more information, please visit `https://nces.ed.gov/ipeds/about-ipeds`.

[2]I refer to Table A2 in Nordin et al. (2010) to build Table C.1. Table A2 in Nordin et al. (2010) shows the matrix of fields of education–occupations matching. The matrix displays the relationship between each field of education and 34 occupations. I assign occupations to each degree field according to the job titles of the matrix.

Table 3.1: Descriptive Statistics

% of mismatch	Males	Females
All	57.1	56.1
Age:		
23-45	57.3	56.5
46-65	56.7	55.4
Field of education:		
Agriculture/natural resources	77.1	86.6
Biology and life sciences	80.7	68.5
Business	35.0	42.1
Communication	79.6	79.6
Computer and information sciences	39.1	56.1
Education	58.1	38.4
Engineering	49.7	58.8
Health professions	40.1	24.4
History	87.5	80.7
English/foreign languages	80.4	74.0
Law	86.7	63.2
Math and statistics	65.5	75.7
Physical sciences/nuclear technologies	84.5	85.6
Psychology	88.4	84.1
Philosophy and religion studies	78.8	87.7
Social sciences	91.2	90.2
N	1,747,964	1,852,967

Notes: The sample comes from ACS 2011-2019 and is restricted to college graduates (not including advanced degrees) aged 23-65 in each round of survey. The shares of mismatch are weighted by personal weight.

The shares of mismatch are 57.1% and 56.1% for males and females, respectively. Business, computer and information sciences, engineering, and health professions are the degree fields that have relatively lower shares of mismatch for males. On the other hand, females with a degree in business, education, and health professions are less likely to have mismatched occupations. For papers using objective measures of mismatch, the shares of mismatch range from 40% to 60%. The proportion of mismatch for vocational graduates in Béduwé and Giret (2011) is 59%. In addition, Malamud (2010) shows the shares of mismatch for college graduates are 44%, 50%, and 63%, respectively, using very broad, broad, and narrow classification approaches.

Aside from IPEDS data, I also use data from Occupational Employment and Wage Statistics (OEWS) program administered by the Bureau of Labor Statistics and State Workforce Agencies to explore the demand for college graduates by examining the local employment across occupations. The OEWS data provide occupational employment across industries at the national and state levels.

I use OEWS 2011-2019 to be consistent with the sample period of ACS and IPEDS.

To build my measure of import exposure and its instrumental variable, I also employ data from a variety of sources. I use trade data from the United Nations Comtrade Database (UN comtrade) and Schott (2008). For employment in local labor markets across industries, I utilize raw data from County Business Pattern (CBP) and imputed county-level data from Eckert et al. (2020b). To evaluate import exposure faced by non-manufacturing sector industries, I further use the 1997 input-output table from the Bureau of Economic Analysis (BEA).

3.4 Empirical Strategy

3.4.1 Measure of Import Exposure

To gauge the degree of import exposure at the local labor market level, I refer to the measure in Autor, Dorn, and G. Hanson (2013). Moreover, I also use the concept of an input-output table in Acemoglu et al. (2016) to account for sectoral linkages, and so indirect trade shocks experienced by an industry's buyers and suppliers can also be included in the measure when calculating import exposure.

$$\text{import}_{j,t^-}^{indirect} = \sum_g \left(w_{g,j}^{up} + w_{g,j}^{down} \right) \text{import}_{g,t^-}. \tag{3.5}$$

Equation 3.5 shows indirect import exposure of industry j, which consists of weighted imports from its buyers and suppliers (denoted by industry g). Here, j and g represent 4-digit NAICS industries, while import_{g,t^-} is U.S. imports of industry g from low-income countries in lagged year t^-.[3] The weights $w_{g,j}^{up}$ and $w_{g,j}^{down}$ respectively capture import exposure that propagates upstream from the buyers and downstream from the suppliers of industry j. For example, if industry g as a buyer accounts for one quarter of the total sales of industry j, then 25% of import exposure faced by industry g in theory would propagate upstream to industry j. On the other hand, if industry g

[3] I combine low-income and lower-middle-income countries together and classify them as the low-income group according to their gross national income (GNI) per capita in 2000: a country belongs to the low-income group if its GNI per capita in 2000 was below \$755; a country belongs to the lower-middle-income group if its GNI per capita in 2000 was between \$755 and \$2994.

as a supplier makes up 30% of industry j's total factor payments, then 30% of import exposure experienced by industry g would propagate downstream to industry j.[4] The example, however, only shows the indirect impact from the first-layer of purchasing and supplying industries. There might be further indirect effects from the second-layer buyers and suppliers and so on (e.g., a buyer's buyers or a supplier's suppliers). To consider full downstream and upstream impacts, these weights are derived by using the Leontief inverse of the 1997 input-output matrix according to the methodology in Acemoglu et al. (2016).[5]

$$\mathrm{IMP}_{s,t^-} = \sum_{j \in J} \left[\frac{L_{s,j,t^-}}{L_{j,t^-}} \frac{\left(\mathrm{import}_{j,t^-}^{direct} + \mathrm{import}_{j,t^-}^{indirect} \right)}{L_{s,t^-}} \right] \tag{3.6}$$

Following the method in Autor, Dorn, and G. Hanson (2013), equation 3.6 measures import exposure at local labor market level s and accounts for both direct and indirect trade shocks of each industry. In this paper, s represents Consistent Public Use Microdata Areas (CPUMAs), which are the smallest and consistent geographic units identified in ACS.[6] J is the set of industries that includes 86 manufacturing and 85 non-manufacturing ones. L_{s,j,t^-} is the employment of industry j in CPUMA s; L_{j,t^-} stands for the total employment of industry j in the U.S.; and L_{s,t^-} refers to the working age population in s. To derive these employment variables, I use the averages of lagged local employment.[7] Here, $\frac{L_{s,j,t^-}}{L_{j,t^-}}$ implies the relative importance of a CPUMA for industry j compared to other areas since the magnitude of the fraction suggests the share of workers of industry j located in s. Lastly, $\mathrm{import}_{j,t^-}^{direct}$ is U.S. imports of industry j from low-income countries and considered a direct trade shock faced by j, while $\mathrm{import}_{j,t^-}^{indirect}$ as stated in equation 3.5 is indirect trade shocks from j's buyers and suppliers.

According to Federal Reserve Economic Data (FRED), the average proportion of employment in U.S. manufacturing through the 2000s is 11.6%, which implies that roughly 90% of working-

[4] In the input-output table, an industry's total sales are equal to its total factor payments.

[5] Acemoglu et al. (2016) use the 1992 input-output table. To be consistent with NAICS industry codes, I follow his methodology and apply the 1997 version of input-output table to compute the weights instead.

[6] Since the definition of PUMAs changes after each decennial census, CPUMAs provide a consistent definition of geographical units across different rounds of ACS after 2000.

[7] For example, if t^- was 2000, then I use the averages of local employment from 1996 through 2000.

age population have a job in non-manufacturing industries. Equation 3.6 therefore might not accurately capture the level of import exposure experienced by most people since IMP_{s,t^-} simply adds up import exposure across industries at the local level, which might overestimate trade shocks of manufacturing. To account for disproportionate employment across manufacturing and non-manufacturing sectors, I derive a measure of weighted trade shocks across the two sectors at the CPUMA level.

$$\widetilde{\text{IMP}}_{s,t^-} = \phi_s^{\text{mfg}} \times \text{IMP}_{s,t^-}^{\text{mfg}} + \phi_s^{\text{nonmfg}} \times \text{IMP}_{s,t^-}^{\text{nonmfg}} \tag{3.7}$$

Equation 3.7 shows the measure of import exposure that accounts for the shares of the two sectors at the CPUMA level. Here, ϕ_s^{mfg} and ϕ_s^{nonmfg} represent the shares of the manufacturing and non-manufacturing sectors in CPUMA s. I use 1998-2000 CBP data to obtain the shares. To construct $\text{IMP}_{s,t^-}^{\text{mfg}}$ and $\text{IMP}_{s,t^-}^{\text{nonmfg}}$, I use equation 3.6 and restrict j to the manufacturing and non-manufacturing sectors, respectively. $\text{IMP}_{s,t^-}^{\text{mfg}}$ stands for import exposure faced by the manufacturing sector in s, while $\text{IMP}_{s,t^-}^{\text{nonmfg}}$ represents import exposure experienced by the non-manufacturing sector in s. By using $\widetilde{\text{IMP}}_{s,t^-}$, I can more precisely gauge the level of import exposure at the CPUMA level.

3.4.2 Instrumental Variable

A concern for my measure is that an increase in imports could be due to either American people's demand for foreign products or foreign countries' productivity growth. To extract only the supply-driven imports and discard the demand-driven part, I refer to Autor, Dorn, and G. Hanson (2013) and Acemoglu et al. (2016) and build a similar instrumental variable for my measure. Equations 3.8-3.10 show how I construct my instrumental variable step by step.

$$\text{import}_{j,t^-}^{indirect\_Oth} = \sum_g \left(w_{g,j}^{up} + w_{g,j}^{down} \right) \text{import}_{g,t^-}^{Other}. \tag{3.8}$$

Instead of using U.S. imports, I use eight high-income countries' imports from low-income countries, $\text{import}_{g,t^-}^{Other}$, to derive indirect import exposure, $\text{import}_{j,t^-}^{indirect\_Oth}$, in equation 3.8.[8]

$$\text{IMP}_{s,t^-}^{Other} = \sum_{j \in J} \left[\frac{L_{s,j,t^-}}{L_{j,t^-}} \frac{\left(\text{import}_{j,t^-}^{direct\_Oth} + \text{import}_{j,t^-}^{indirect\_Oth}\right)}{L_{s,t^-}} \right] \tag{3.9}$$

Eight high-income countries' imports are also used as direct trade shocks $\text{import}_{j,t^-}^{direct\_Oth}$ and combined with indirect import exposure $\text{import}_{j,t^-}^{indirect\_Oth}$ to derive $\text{IMP}_{s,t^-}^{Other}$.

$$\widetilde{\text{IMP}}_{s,t^-}^{Other} = \phi_s^{\text{mfg}} \times \text{IMP}_{s,t^-}^{\text{mfg}\_Oth} + \phi_s^{\text{nonmfg}} \times \text{IMP}_{s,t^-}^{\text{nonmfg}\_Oth} \tag{3.10}$$

Equation 3.10 lastly shows the instrumental variable for $\widetilde{\text{IMP}}_{s,t^-}$ in equation 3.7. The sector-specific measure of import exposure ($\text{IMP}_{s,t^-}^{\text{mfg}\_Oth}$ and $\text{IMP}_{s,t^-}^{\text{nonmfg}\_Oth}$) is constructed by using $\text{IMP}_{s,t^-}^{Other}$ in equation 3.9.

3.4.3 Econometric Specifications

In this subsection I present main specifications for estimating the impacts of import exposure on education-job mismatch, supply of college graduates, and occupational employment matched with each degree field.

$$\text{Mismatch}_{ijkst} = \alpha + \beta \widetilde{\text{IMP}}_{s,t^-} + \text{Individual}_i \rho + T \times \phi_s + \phi_s + \phi_k + \phi_j + \varepsilon_{ijkst}. \tag{3.11}$$

Equation 3.11 shows the baseline specification for estimating the effect of import exposure on education-job mismatch by using ACS data. Mismatch_{ijkst} is dichotomous and equal to 1 if individual i's field of education does not match her occupation in year t and equal to 0 otherwise. I employ the linear probability model for estimation. $\widetilde{\text{IMP}}_{s,t^-}$ is the measure of import exposure in

[8]The eight high-income countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

CPUMA s in lagged time period t^{-}, and CPUMA s is where i lived at the time of survey. Here, I use the average of two-year and three-year lagged measures of import exposure in my main specification. Individual_i is a vector of individual characteristics including genders, races, states of birth, first and second fields of education, and birth years. I also include CPUMA-specific linear time $T \times \phi_s$ to control for any time-varying unobservables at the CPUMA level. ϕ_s represents CPUMA fixed effects and is used to account for time-invariant unobservables such as geographical, cultural, and resource differences across CPUMAs. Since each occupation requires different qualifications, some professions have a relatively high threshold such as engineers and physicians, while others like sales-related jobs have a relatively low-entry threshold. To account for huge heterogeneity across occupations, I include ϕ_k occupation fixed effects. ϕ_j is added to the model to control for occupational composition within each industry. Standard errors are clustered on CPUMA to allow for serial correlation among individuals within CPUMAs.

$$\text{Graduates}_{imst} = \alpha + \beta \widetilde{\text{IMP}}_{s,t^{-}} + T \times \phi_s + \phi_s + T \times \phi_i + \phi_i + \varepsilon_{imst}. \tag{3.12}$$

To explore how the supply of college graduates is impacted by trade shocks, I use equation 3.12 as the baseline specification. Graduates_{imst} is the log of the number of bachelor's degrees in field m awarded in 4-year college i. Here, I use the number of bachelor's degrees awarded as a proxy for the supply of college graduates. Since IPEDS does not have information on when students selected their majors, I use the year of degree awarded as a reference point and assume that students decided on their fields of education in year t, which is 4-year lagged relative to the year of degree awarded.[9] CPUMA s represents the location of college i. $\widetilde{\text{IMP}}_{s,t^{-}}$ captures import exposure in s in lagged time period t^{-}. Similarly, I include CPUMA-specific linear time trend $T \times \phi_s$ to control for unobserved time-varying factors such as educational resources and the number of high school students across CPUMAs. ϕ_s is CPUMA fixed effects. To account for time-invariant characteristics of each school, the college fixed effects ϕ_i are included in the model. Since some factors such as the number of professors, annual budget, and admission standards might change over time and affect

[9]For example, if students graduated in 2015, then they were assumed to choose their majors in 2011.

my results, institution-specific linear time trend $T \times \phi_i$ is further added to the model. Considering the characteristics of panel data and correlation of schools within CPUMAs, equation 3.12 uses two-way clustered standard errors to account for serial correlation in two different dimensions. Standard errors are clustered on CPUMA and school to allow for serial correlation within schools over time and among schools within the same geographical area.

$$\text{Employment}_{mst} = \alpha + \beta \widetilde{\text{IMP}}_{s,t^-} + T \times \phi_s + \phi_s + \varepsilon_{mst}. \tag{3.13}$$

Equation 3.13 is the baseline specification for evaluating the import exposure's effect on demand for college graduates. Here, I use occupational employment matched with each degree field as proxies for demand. Using employment as a measure of labor demand is not uncommon in the literature (Krishna et al. 2001; Morrison Paul and Siegel 2001; Popov and Rocholl 2018; Slaughter 2001). OEWS data provide state-level employment across occupations. Moreover, I use ACS to impute CPUMA-level employment. For example, the matched occupations for psychology are psychologists, counselors, and social workers according to Table C.1. I derive imputed CPUMA-level employment of these occupations and then use imputed employment as demand for college graduates in psychology. While occupational employment might not be a very accurate index of demand for college graduates, it could still be viewed as overall job opportunities for different fields of education. Employment_{mst} is the log employment of occupations matched with degree field m in CPUMA s in year t. $\widetilde{\text{IMP}}_{s,t^-}$ is the measure of import exposure in s in lagged time period t^-. $T \times \phi_s$ is CPUMA-specific linear time trend, and ϕ_s is CPUMA fixed effects. Standard errors are clustered on CPUMA to allow for correlation within CPUMAs over the time period.

3.5 Results

3.5.1 Education-Job Mismatch

Table 3.2 reports the baseline 2SLS estimates of import exposure's impact on education-job mismatch by using equation 3.11. Columns 1 and 2 present the results when I use the whole sample.

Table 3.2: Impact of Import Exposure on Education-Job Mismatch

	All		Males		Females	
	Coeffs. (1)	S.E. (2)	Coeffs. (3)	S.E. (4)	Coeffs. (5)	S.E. (6)
All fields	0.021***	0.003	0.024***	0.004	0.016***	0.004
Field of education:						
Agriculture/natural resources	0.009	0.008	0.018*	0.010	0.005	0.017
Biology and life sciences	−0.006	0.010	0.003	0.016	−0.007	0.014
Business	0.002	0.002	0.003	0.002	0.002	0.002
Communication	0.019*	0.011	0.010	0.019	0.025	0.017
Computer and info. sciences	0.008	0.011	0.015	0.014	−0.014	0.024
Education	0.004*	0.002	0.007	0.006	0.003	0.002
Engineering	0.014***	0.006	0.014**	0.006	0.025	0.015
Health professions	−0.003	0.004	−0.015	0.012	−0.001	0.004
History	0.005	0.008	0.007	0.009	0.007	0.021
English/foreign languages	0.011	0.010	0.042**	0.020	0.000	0.012
Law	0.037	0.063	0.199	0.228	0.069	0.081
Math and statistics	0.047**	0.023	0.062*	0.036	0.018	0.039
Physics/nuclear tech.	0.007	0.010	−0.007	0.010	0.034*	0.018
Psychology	0.024**	0.010	0.010	0.018	0.024**	0.010
Philosophy and religion	0.018	0.017	0.004	0.019	0.073*	0.039
Social sciences	0.022***	0.008	0.010	0.011	0.028**	0.013

Notes: Standard errors (S.E.) are robust to heteroskedasticity and clustered on CPUMA. CPUMA-specific linear time trend, CPUMA, occupation, industry, and age cohort fixed effects are included. When the sample includes all fields of education, respondents' first and second fields of education are included in the specification as controls. All import data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

In addition to using the whole sample of ACS, I also differentiate between males and females in columns 4-6 to explore heterogeneity since the career path and choice of college major could differ significantly across genders (Canes and Rosen 1995; Polachek 1978; Robst 2007a; Zafar 2013). The first row shows the general effects of import exposure on education-job mismatch. For the whole sample, the estimate suggests that import exposure significantly increases the probability of education-job mismatch during 2011-2019. Since import exposure increases by roughly $1,000 per person from 2011 through 2019 by using the measure in equation 3.7, a $1,000 per person increase in import exposure predicts a rise in the probability of mismatch by 2.1 percentage points. When I divide my sample into female and male subsamples, males are more impacted regarding education-job mismatch. A $1,000 increase in import exposure is associated with increases in the probability of mismatch by 2.4 and 1.6 percentage points, respectively, for males and females. For the rest of this paper, I assume that the change in import exposure is \$1,000 per person (i.e.,$\Delta \widetilde{\text{IMP}} = 1000$) when calculating the effects of trade shocks.

Due to huge heterogeneity across fields of education, I classify college majors into 16 categories and examine import exposure's effect on education-job mismatch for each of them. Table 3.2 shows that the probability of mismatch for males in the field of agriculture/natural resources significantly increases by 0.9 percentage points due to trade shocks. In addition, the impact is only statistically significant for males, but not for females. People in the field of communication are also more likely to be mismatched due to import exposure. However, the effect is less pronounced as the estimate is statistically significant at the 10% level, and neither the male subsample nor female subsample show a significant result. For education, the estimate is barely significant at the 10% level, and the magnitude is relatively small (0.4 percentage point). Both males and females also do not show significant results. Engineering, on the other hand, is statistically significant at the 1% level and associated with a 1.4 percentage point increase in the probability of mismatch. Exploring heterogeneity across genders, I find that males in engineering are predicted to face a rise in the probability of mismatch by 1.4 percentage points given a \$1,000 per person increase in import exposure. For English/foreign languages, the associated effect for males is a 4.2 percentage point increase in the probability of mismatch. The table also suggests that increased import exposure in the 2010s has a non-trivial negative effect on the probability of education-job match for people with a degree in math and statistics. The associated effect for math and statistics is a 4.7 percentage point increase in the probability of mismatch. Compared to females, males are more likely to be mismatched in math and statistics since a \$1,000 per person increase in import exposure predicts a rise in the probability of mismatch by 6.2 percentage points. For psychology and social sciences, the mismatch probabilities significantly increase due to import exposure. The estimates are associated with 2.4 and 2.2 percentage point increases in the probabilities for psychology and social sciences, respectively. Moreover, these two fields suggest that the negative effect of trade shocks on education-job mismatch is more pronounced for females since only the female subsample shows significant estimates.

Table 3.3: Impact of Import Exposure on Education-Job Mismatch by Age Group

	Aged 23-45		Aged 46-65	
	Coeffs. (1)	S.E. (2)	Coeffs. (3)	S.E. (4)
All fields	0.024^{***}	0.004	0.018^{***}	0.005
Field of education:				
Agri./natural resources	0.009	0.013	0.005	0.014
Biology and life sci.	−0.008	0.013	0.004	0.018
Business	0.003	0.002	0.003	0.003
Communication	0.019	0.014	0.007	0.019
Computer and info. sci.	0.001	0.013	0.017	0.021
Education	0.002	0.003	0.006	0.003
Engineering	0.022^{***}	0.007	0.002	0.009
Health professions	−0.001	0.005	−0.004	0.005
History	0.016	0.014	0.003	0.017
Languages	0.008	0.014	0.010	0.016
Law	−0.032	0.091	0.388	0.313
Math and statistics	0.007	0.038	0.083^{**}	0.034
Physics/nuclear tech.	0.014	0.012	0.009	0.016
Psychology	0.027^{**}	0.013	0.018	0.020
Philosophy and religion	0.048^{*}	0.026	−0.004	0.027
Social sciences	0.019	0.012	0.026^{*}	0.013

Notes: Standard errors (S.E.) are robust to heteroskedasticity and clustered on CPUMA. CPUMA-specific linear time trend, CPUMA, occupation, industry, and age cohort fixed effects are included. When the sample includes all fields of education, respondents' first and second fields of education are included in the specification as controls. All import data are in 2007 US\$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Considering the differential effects across age groups, I divide the ACS sample into younger (aged 23–45) and older (aged 46-65) age groups to explore impacts of import exposure on mismatch for each group in Table 3.3. The estimates in the first row suggest that import exposure has a stronger effect for the younger people as the associated effects are 2.4 and 1.8 percentage points, respectively, for the younger and older age groups. Comparing Tables 3.2 and 3.3, I find that the effects of import exposure on mismatch are more pronounced for younger people in engineering and psychology, but more significant for older people in math and social sciences.

Considering differential effects across genders, I also explore impacts of import exposure on mismatch, respectively, for males and females across younger and older age groups in Table 3.4. The first row shows the overall effects on education-job mismatch by pooling all fields of education together. For males, the younger group is more impacted by trade shocks compared to the older

Table 3.4: Impact of Import Exposure on Education-Job Mismatch by Age Group across Genders

	Males				Females			
	23-45		46-65		23-45		46-65	
	Coeffs. (1)	S.E. (2)	Coeffs. (3)	S.E. (4)	Coeffs. (5)	S.E. (6)	Coeffs. (7)	S.E. (8)
All fields	0.031***	0.006	0.014**	0.007	0.015***	0.005	0.018***	0.006
Field of education:								
Agri./natural resources	0.031	0.020	−0.008	0.016	−0.024	0.021	0.048	0.032
Biology and life sci.	0.001	0.023	−0.007	0.029	−0.004	0.017	−0.013	0.028
Business	0.004	0.003	0.002	0.003	0.002	0.002	0.003	0.004
Communication	−0.006	0.027	−0.007	0.032	0.032	0.020	−0.007	0.035
Computer and info. sci.	0.009	0.016	0.022	0.031	−0.053	0.046	0.007	0.041
Education	0.000	0.007	0.010	0.008	0.002	0.003	0.003	0.004
Engineering	0.023***	0.009	−0.001	0.009	0.016	0.018	0.008	0.041
Health professions	0.003	0.018	−0.025	0.019	0.000	0.005	−0.002	0.005
History	−0.001	0.014	0.031	0.021	0.036	0.026	−0.027	0.047
Languages	0.027	0.025	0.061	0.045	0.000	0.018	0.006	0.021
Law	−0.147	0.367	−0.108	0.090	0.126	0.104	0.311	0.379
Math and statistics	0.089	0.070	0.081	0.055	−0.077	0.075	0.076	0.069
Physics/nuclear tech.	−0.004	0.017	−0.019	0.018	0.027	0.026	0.039	0.024
Psychology	0.021	0.027	0.007	0.035	0.027*	0.014	0.019	0.025
Philosophy and religion	0.014	0.036	−0.006	0.031	0.150*	0.084	−0.022	0.068
Social sciences	0.000	0.016	0.027	0.020	0.029	0.018	0.020	0.019

Notes: Standard errors (S.E.) are robust to heteroskedasticity and clustered on CPUMA. CPUMA-specific linear time trend, CPUMA, occupation, industry, and age cohort fixed effects are included. When the sample includes all fields of education, respondents' first and second fields of education are included in the specification as controls. All import data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

group. The associated effect for younger males is an increase in the probability of mismatch by 3.1 percentage points, which is more than twice the effect faced by older males. Older females, on the other hand, encounter a slightly stronger effect of import exposure on mismatch relative to younger females.

Table 3.4 also shows heterogeneity across fields of study. I find that the effects of import exposure are less statistically significant in most fields of education compared to Table 3.2. For younger males, only engineering suggests a relatively significant effect of import exposure on mismatch. The probability of mismatch for younger males with a degree in engineering goes up by 2.3 percentage points if there is a $1,000 per person increase in import exposure. However, I do not observe any statistically significant results for the older male group in other fields of education. For younger females, psychology and philosophy are the two fields where they are more likely to face a mismatch due to trade shocks. Moreover, the magnitude of the estimate for philosophy is twice as large as its counterpart in Table 3.2. Similar to the older male group, older females, do not exhibit any statistically significant results in any fields of education. The reduced significance level could be due to sample sizes when I divide ACS data into smaller subsamples.

3.5.2 Supply of College Graduates

In this subsection, I use IPEDS data to explore whether import exposure has any effect on the supply of college graduates at the institutional level. Equation 3.12 is the baseline model for estimating the impact. I treat the number of bachelor's degrees awarded in a 4-year college as a proxy for the supply of college graduates across fields of education.

Table 3.5: Impact of Import Exposure on the Supply of College Graduates

	All		Males		Females	
	Coeffs. (1)	S.E. (2)	Coeffs. (3)	S.E. (4)	Coeffs. (5)	S.E. (6)
All fields	0.083***	0.022	0.071***	0.018	0.079***	0.023
Field of education:						
Agriculture/natural resources	0.107***	0.042	0.090***	0.033	0.142***	0.040
Biology and life sciences	0.080***	0.018	0.149***	0.026	0.050**	0.019
Business	−0.013	0.013	−0.026*	0.015	−0.038**	0.015
Communication	0.079***	0.023	0.087***	0.026	0.060**	0.027
Computer and info. sciences	0.016	0.022	0.010	0.022	−0.058	0.038
Education	0.037	0.031	0.077**	0.035	0.018	0.030
Engineering	0.035*	0.018	0.030	0.019	−0.071***	0.026
Health professions	0.184***	0.055	0.167***	0.048	0.175***	0.046
History	0.122***	0.025	0.117***	0.025	0.078***	0.028
English/foreign languages	0.129***	0.032	0.137***	0.032	0.114***	0.025
Law	0.395***	0.094	0.259**	0.124	0.317***	0.099
Math and statistics	0.115***	0.025	0.082***	0.029	0.140***	0.033
Physics/nuclear tech.	0.129***	0.027	0.147***	0.026	0.051*	0.028
Psychology	0.156***	0.025	0.246***	0.030	0.142***	0.022
Philosophy and religion	0.094***	0.030	0.101***	0.031	0.058*	0.034
Social sciences	0.044	0.027	0.078**	0.035	0.022	0.022

Notes: Standard errors (S.E.) are robust to heteroskedasticity and two-way clustered on CPUMA and school. CPUMA-specific linear time trend, CPUMA, school-specific linear time trend, and school fixed effects are included. All import data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Table 3.5 shows how the supply of college graduates reacts to trade shocks. The recipients of bachelor's degrees in the table include both U.S. and non-U.S. (nonresident alien) students. The estimates in the first row suggest that import exposure has a strong positive effect on the number of college degrees awarded as a whole. A $1,000 per person rise in import exposure is predicted to increase the number of bachelor's degrees awarded in a 4-year college by 8.3%. Moreover, the numbers of college degrees awarded to both male and female students also significantly increase by 7.1% and 7.9%, respectively. Table 3.5 further presents how the supply of college graduates is affected in each field of education. Column 1 suggests that the numbers of bachelor's degree recipients pronouncedly increase in most fields of education due to import exposure. The 12 degree fields suggest significant increases in the numbers of bachelor's degrees awarded. Only business, computer science, education, and social sciences do not suggest a positive response to increased import exposure. Columns 3 and 5 similarly show that there is a pronounced increase in the numbers of college degrees awarded to both males and females in most fields of education. Business, however, suggests an opposite outcome compared to other fields. The estimates of business are associated with decreases in the numbers of degrees awarded to males and females by 2.6% and 3.8%, respectively. In addition, the estimates of education and social sciences are statistically significant in column 3, but not in column 5, which implies that males are more driven by import exposure to choose education and social sciences compared to females.

A concern for the results in Table 3.5 is the potential effects from immigrant students, since exposure from foreign students might potentially impact students' decisions on fields of education (Orrenius and Zavodny 2015). For a robustness check, Table 3.6 presents results by restricting degree completion data to U.S. citizens. I find that results in Table 3.6 are qualitatively the same as their counterparts in Table 3.5. The numbers of bachelor's degrees awarded still significantly increase in most fields of education.

In the appendix, I further derive the total number of bachelor's degrees awarded at the CPUMA level by adding up numbers from 4-year colleges in each CPUMA. Table C.3 shows the effects of import exposure on the supply of college graduates at the CPUMA level. The table shows that the numbers of college degrees awarded in most fields of study still pronouncedly increase due to rising import exposure. The estimates in the first row (all fields), however, are not as statistically

Table 3.6: Impact of Import Exposure on the Supply of College Graduates - U.S. Citizens

	All		Males		Females	
	Coeffs. (1)	S.E. (2)	Coeffs. (3)	S.E. (4)	Coeffs. (5)	S.E. (6)
All fields	0.088***	0.023	0.077***	0.019	0.082***	0.024
Field of education:						
Agriculture/natural resources	0.112***	0.035	0.087***	0.033	0.137***	0.045
Biology and life sciences	0.087***	0.019	0.156***	0.015	0.057***	0.020
Business	−0.015	0.013	−0.022	0.002	−0.048***	0.015
Communication	0.086***	0.023	0.091***	0.026	0.059**	0.026
Computer and info. sciences	0.026	0.023	0.023	0.023	−0.056	0.039
Education	0.037	0.031	0.078**	0.035	0.016	0.029
Engineering	0.037**	0.018	0.035*	0.018	−0.078***	0.026
Health professions	0.188***	0.056	0.170***	0.050	0.178***	0.046
History	0.127***	0.026	0.123***	0.025	0.077***	0.028
English/foreign languages	0.127***	0.032	0.133***	0.031	0.113***	0.025
Law	0.349***	0.091	0.180	0.116	0.290***	0.096
Math and statistics	0.125***	0.026	0.101***	0.030	0.148***	0.033
Physics/nuclear tech.	0.130***	0.027	0.152***	0.026	0.057**	0.029
Psychology	0.157***	0.024	0.248***	0.029	0.142***	0.022
Philosophy and religion	0.094***	0.030	0.100***	0.031	0.060*	0.034
Social sciences	0.039	0.026	0.080**	0.035	0.020	0.022

Notes: Standard errors (S.E.) are robust to heteroskedasticity and two-way clustered on CPUMA and school. CPUMA-specific linear time trend, CPUMA, school-specific linear time trend, and school fixed effects are included. All import data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

significant as their counterparts in Tables 3.5 and 3.6.

3.5.3 Demand for College Graduates

In this subsection, I use OEWS 2011-2019 to explore the impact of import exposure on the demand for college graduates at the local labor market level. Equation 3.13 is the baseline specification for estimation. According to Table C.1, each field of education matches with certain occupations. I then impute occupational employment at the local level and treat imputed employment as a rough measure of demand for college graduates in each field.

Table 3.7 shows the effects of import exposure on imputed occupational employment for each field of education at the CPUMA and state levels. The estimates for business are statistically significant and positive in columns 1 and 3, implying business-related employment is positively impacted by trade shocks. A $1,000 per person rise in import exposure predicts an increase in

Table 3.7: Impact of Import Exposure on Occupational Employment

	CPUMA		State	
	Coeffs. (1)	S.E. (2)	Coeffs. (3)	S.E. (4)
Field of education:				
Agri./natural resources	−0.014	0.014	−0.049	0.059
Biology and life sci.	−0.019	0.012	−0.041	0.059
Business	0.027**	0.013	0.021***	0.007
Communication	0.044	0.031	0.018	0.018
Computer and info. sci.	0.021	0.025	−0.008	0.025
Education	−0.021	0.018	0.007	0.015
Engineering	−0.034**	0.014	−0.017	0.020
Health professions	−0.023*	0.013	0.019*	0.010
History	−0.015	0.021	0.009	0.017
Languages	−0.023	0.018	0.005	0.015
Law	−0.067	0.086	0.054	0.045
Math and statistics	0.021	0.025	−0.008	0.025
Physics/nuclear tech.	−0.010	0.020	−0.043	0.063
Psychology	−0.084**	0.039	−0.053**	0.025
Philosophy and religion	0.077	0.086	−0.114	0.242
Social sciences	0.021	0.026	−0.035	0.054

Notes: Standard errors (S.E.) are robust to heteroskedasticity and clustered on CPUMA/state. CPUMA-/state-specific linear time trend, CPUMA/state, fixed effects are included. All import data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

the employment of occupations matched with the business field by 2.7% and 2.1% at the CPUMA and state levels, respectively. For engineering, while the coefficient estimates are negative in both columns 1 and 3, only CPUMA-level employment is significantly affected by import exposure. The associated effect is a decrease in the employment of engineering-related jobs by 3.4%. The employment of occupations matched with health professions, however, suggests a discrepancy between CPUMAs and states. While import exposure has a negative effect on CPUMA-level jobs in health professions, the employment at the state level is positively impacted by trade shocks. The effect of import exposure on the employment of occupations matched with psychology, on the other hand, is consistent across the CPUMA and state levels. The estimates are associated with decreases in psychology related employment by 8.4% and 5.3%, respectively, at the CPUMA and state levels. According to results in Table 3.7, import exposure does not have a significant impact on occupational employment for most fields of education except business, engineering, health professions, and psychology.

Table 3.8: Impact of Import Exposure on Occupational Employment of College Graduates

	CPUMA		State	
	Coeffs. (1)	S.E. (2)	Coeffs. (3)	S.E. (4)
Field of education:				
Agri./natural resources	−0.031*	0.016	−0.122*	0.072
Biology and life sci.	−0.031*	0.013	−0.082	0.054
Business	0.010	0.013	0.018	0.044
Communication	0.046	0.031	0.006	0.064
Computer and info. sci.	−0.008	0.025	0.029	0.082
Education	−0.022	0.019	−0.004	0.050
Engineering	−0.047***	0.014	−0.004	0.040
Health professions	−0.042***	0.015	−0.023	0.048
History	−0.014	0.023	−0.007	0.056
Languages	−0.029	0.019	−0.004	0.050
Law	0.090	0.111	0.293	0.255
Math and statistics	−0.008	0.025	0.029	0.082
Physics/nuclear tech.	−0.024	0.023	−0.143	0.114
Psychology	−0.074*	0.044	−0.186**	0.092
Philosophy and religion	0.130	0.079	0.154	0.404
Social sciences	0.024	0.032	−0.139*	0.073

Notes: Standard errors (S.E.) are robust to heteroskedasticity and clustered on CPUMA/state. CPUMA-/state-specific linear time trend, CPUMA/state, fixed effects are included. All import data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Besides looking at the impact on the overall occupational employment for each field of education, I also explore whether import exposure affects the employment of college graduates. Table 3.8 presents the effects of import exposure on the imputed occupational employment of college graduates in each field of education at the CPUMA and state levels. The estimates for agriculture/natural resources suggest that import exposure has a negative effect on the employment of occupations matched with agriculture/natural resources at the CPUMA and state levels. The employment of biology-related occupations is also negative affected at the CPUMA level. Consistent with the results in Table 3.7, the occupational employment of college graduates in engineering, health professions, and psychology significantly decreases at the CPUMA level due to trade shocks. Moreover, I find that the estimates for business are not as statistically significant as their counterparts in Table 3.7.

3.5.4 Summary of Empirical Results

Table 3.9: Summary of the Effects of Import Exposure from Previous Tables

	Mismatch			Supply (Number of B.A. degrees)			Demand (Occ. employment)	
	All (1)	Males (2)	Females (3)	All (4)	Males (5)	Females (6)	CPUMA (7)	State (8)
All fields	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	$+^{***}$	N/A	N/A
Field of education:								
Agri./natural resources	$+$	$+^{*}$	$+$	$+^{***}$	$+^{***}$	$+^{***}$	$-$	$-$
Biology and life sci.	$-$	$+$	$-$	$+^{***}$	$+^{***}$	$+^{**}$	$-$	$-$
Business	$+$	$+$	$+$	$-$	$-^{*}$	$-^{**}$	$+^{**}$	$+^{***}$
Communication	$+^{*}$	$+$	$-$	$+^{***}$	$+^{***}$	$+^{**}$	$+$	$+$
Computer and info. sci.	$+$	$+$	$+$	$+$	$+$	$-$	$+$	$-$
Education	$+^{*}$	$+$	$+$	$+$	$+^{**}$	$+$	$-$	$+$
Engineering	$+^{***}$	$+^{**}$	$+$	$+^{*}$	$+$	$-^{***}$	$-^{**}$	$-$
Health professions	$-$	$-$	$-$	$+^{***}$	$+^{***}$	$+^{***}$	$-^{*}$	$+^{*}$
History	$+$	$+$	$+$	$+^{***}$	$+^{***}$	$+^{***}$	$-$	$+$
Languages	$+$	$+^{**}$	$+$	$+^{***}$	$+^{***}$	$+^{***}$	$-$	$+$
Law	$+$	$+$	$+$	$+^{***}$	$+^{***}$	$+^{***}$	$-$	$+$
Math and statistics	$+^{**}$	$+^{*}$	$+$	$+^{***}$	$+^{**}$	$+^{***}$	$+$	$-$
Physics/nuclear tech.	$+$	$-$	$+^{*}$	$+^{***}$	$+^{***}$	$+^{*}$	$-$	$-$
Psychology	$+^{**}$	$+$	$+^{**}$	$+^{***}$	$+^{***}$	$+^{***}$	$-^{**}$	$-^{**}$
Philosophy and religion	$+$	$+$	$+^{*}$	$+^{***}$	$+^{***}$	$+^{*}$	$+$	$-$
Social sciences	$+^{***}$	$+$	$+^{**}$	$+$	$+^{**}$	$+$	$+$	$-$

Notes: + and − represent the signs of the coefficient estimates. Columns 1-3 are from Table 3.2. Columns 4-6 are from Table 3.5. Columns 7-8 are from Table 3.7. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

To examine the role of demand for and supply of college graduates in education-job mismatch, I summarize the results from previous tables and show the signs of coefficient estimates in Table 3.9. The signs in columns 1-3 are from Table 3.2 and show the effects of import exposure on education-job mismatch. The signs in columns 4-6 are from Table 3.5 and present the effects of import exposure on the number of bachelor's degrees awarded. The signs in columns 7-8 come from Table 3.7 and show the effects of import exposure on occupational employment matched with each field of education.

According to Table 3.9, the rise in the probability of education-job mismatch as a whole could be partially explained by a strong increase in the number of bachelor's degrees awarded due to trade shocks, since import exposure significantly increases the supply of college graduates, but most occupational employment matched with each field of education does not exhibit a corresponding increase to absorb the surge of college graduates.

3.6 Conclusions

This paper presents the impacts of import exposure on education-job mismatch from 2011 through 2019. I first set up a matching function to elaborate the conceptual framework behind mismatch. The original matching function hinges on job vacancies and unemployed workers to determine the probability of job matching. The modified matching function in this paper implies that the probability of match in each field is determined by the direction and relative magnitude of changes in the demand for and supply of college graduates due to trade shocks.

In this paper I use ACS data to empirically examine whether import exposure has any effect on the probability of education-job mismatch. To quantify the magnitude of import exposure, I use the concept of input-output tables to construct a measure that captures import exposure faced by both manufacturing and non-manufacturing sectors at the CPUMA level. I find that import exposure significantly increases the probability of education-job mismatch. A \$1,000 per person increase in import exposure leads to a rise in the probability of mismatch by 2.1 percentage points. When I split the sample into females and male subsamples, the results suggest that males and females respectively face increases in the probability of mismatch by 2.4 and 1.6 percentage points.

As for the supply of college graduates, I use the number of bachelor's degrees awarded as a proxy and investigate import exposure's effect on the supply of college graduates at the institutional level. My results show that the number of college degrees awarded significantly increases by 8.3% in a 4-year college due to increased import exposure in the 2010s. Moreover, of the 16 degree fields, 12 of them exhibit strong increases in the numbers of degrees awarded. I also find that the numbers of bachelor's degrees awarded to males and females respectively increase by 7.1% and 7.9% at the institutional level. To evaluate the demand for college graduates, I look at employment of occupations matched with each field of education at the CPUMA and state levels. For most degree fields, the results do not show that their matched occupational employment is significantly affected by import exposure. For engineering, health professions, and psychology, these degree fields face decreases in their matched occupational employment due to trade shocks.

Combining my empirical results, the overall increase in the probability of education-job mismatch could be explained by the unbalanced demand and supply of college graduates. The pronounced increases in the supply of college graduates across fields of education are not accompanied by corresponding rises in the employment of their matched occupations.

APPENDICES

APPENDIX A

APPENDIX TO CHAPTER ONE

A.1 Predicted Imports from the Gravity Model

Another potential threat to the validity of the instruments comes from the technological changes in the 2000s, which could lead to my results. Even though I already use year fixed effects in the model to control for the overall trend, the technological progress or the application of new technologies in each state could be different in the time period. Moreover, the exclusion restriction of the instruments in the context may not hold due to the entangled nature of trade and technological progress. To tackle the potential violation of my instruments I follow the concepts in Blanchard and Olney (2017) and Feyrer (2019) to obtain predicted U.S. imports from China by using the following equations A.1 and A.2 derived from the gravity model.

$$\log(\text{IMP})_{us,i,t} = \varphi_i + \varphi_t + \varepsilon_{us,i,t}. \tag{A.1}$$

$$\text{predicted import}\,^{CHN}_{US,t} = e^{\tilde{\varphi}_{CHN}+\tilde{\varphi}_t}. \tag{A.2}$$

The variable, $\log(\text{IMP})_{us,t}$, is U.S. imports of the selected industries from country i in year t. φ_i and φ_t are exporting country fixed effects and year fixed effects, respectively.[1] $\varepsilon_{us,i,t}$ is the idiosyncratic error term. After estimating equation A.1, I can use equation A.2 to obtain the predicted U.S. imports of the selected industries from China in year t. Since I only use exporting country and year fixed effects to predict the imports, the predicted imports only contain the time invariant components of exporting countries and the aggregate time trend. Therefore, any time-varying factors in each state of the U.S. that could potentially affect students' decision on major choice are not related to the predicted imports.

[1] The selected industries here refer to the ones shown in Table 1.2.

Table A.1 shows the estimates of 2SLS results by using the predicted imports as new instruments. Panel A of the table suggests that the statistical significance level of each specification decreases. However, the signs of different measures of Chinese import competition are still negative, and the significance level is still at 10%. Panel B reports the first stage of 2SLS. While F statistics become much smaller compared to the ones in Table 1.4, the new instruments still show a strong positive correlation with the potential endogenous variables.

Table A.1: Estimates of 2SLS by Using Predicted Imports.

	A. 2SLS results			
	(1)	(2)	(3)	(4)
(Imports from China to U.S.)/worker (IMP)	−0.0262 (−1.60)			
IMP weighted by migration		-0.0364^{*} (−1.78)		
IMP weighted by migration and workplace			-0.0521^{*} (−1.74)	
IMP weighted by migration and workplace (state of birth)				-0.0537^{*} (−1.73)
IMP weighted by migration and workplace (other states)				−0.0669 (−1.60)
R^2	0.0307	0.0307	0.0307	0.0307
	B. First Stage of 2SLS estimates			
(Predicted imports from China)/worker ($\text{IMP}^{predicted}$)	0.6631^{***} (4.22)			
$\text{IMP}^{predicted}$ weighted by migration		0.6826^{***} (4.39)		
$\text{IMP}^{predicted}$ weighted by migration and workplace			0.6656^{***} (4.21)	
F-Stat	17.79	19.24	17.69	

Notes: Standard errors are robust to heteroskedasticity and clustered on the state of birth. t-statistics are in parentheses. State of birth, state of work, and year fixed effects are included in each column. State-level and additional controls are also included in each column. The number of observations is 182,461. All imports data are in 2007 US$ and values are in thousands. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

A.2 Decision on Attending College

Since Chinese import competition affects high school graduation rates in the U.S. (Greenland and Lopresti 2016), it is possible that the trade shock could further influence students' decisions on pursuing college education. To test whether the trade shock affects students' decisions on going to college, I use a similar econometric model, equation A.3, and the same measures of Chinese import competition and their corresponding instruments as stated in section 1.5 to carry out my estimation. Here, I restrict my sample to people who were aged 23-25, possessed a high school degree and did not enroll in school at the time of PUMS 2009-2017. The dependent variable, $\text{College}_{i,s,t}$, is equal to 1 if individual i had attended college before and equal to 0 otherwise.[2]

$$\begin{aligned} \text{College}_{i,s,t} = \alpha + \beta \text{IMP}_{s,t-2} + \overline{\text{State}}_{s,t}\delta + \text{Individual}_{i,s}\rho \\ + \phi_s + \eta_w + \varphi_t + \varepsilon_{i,s,t}. \end{aligned} \tag{A.3}$$

Columns 1-3 of Table A.2 report the results when I use the imports of selected industries in Table 1.2. The estimated coefficient in each column is at least statistically significant at the 5% level and negative. This implies that the import competition has a negative effect on students' willingness to pursue college education. The estimated coefficient in column 1 is associated with a 0.83 percentage point, or equivalently 1.29%, decrease in the probability of pursuing college education.[3] The associated effects in columns 2 and 3 respectively would be a 0.92 percentage point decrease in column 2 and a 1.05 percentage point decrease in column 3 for the probability of going to college, respectively. Nevertheless, if I do not restrict the imports to the selected industries and use the whole manufacturing sector instead, I do not observe any significant results in columns 4-6.

[2] I also include people who did not finish their college education.

[3] The average proportion of going to college is 64.58% from PUMS. Thus, $0.83\%/(0.83\% + 64.58\%) \approx 1.27\%$.

Table A.2: Decision on Attending College.

Dependent variable:	Selected industries			All industries		
College education	(1)	(2)	(3)	(4)	(5)	(6)
(Imports from China to U.S.)/ worker (IMP)	-0.0327^{***}			0.0007		
	(-2.64)			(0.14)		
IMP weighted by migration		-0.0363^{***}			0.0014	
		(-2.60)			(0.21)	
IMP weighted by migration and workplace			-0.0441^{**}			-0.0055
			(-2.04)			(-0.59)
Year × race fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year × gender fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.041	0.041	0.041	0.041	0.041	0.041
Number of observations	568,919	568,919	568,919	568,919	568,919	568,919

Notes: Standard errors are robust to heteroskedasticity and clustered on the state of birth. t-statistics are in parentheses. State of birth, state of work, and year fixed effects are included in each column. State-level and additional controls are also included in each column. All imports data are in 2007 US$ and values are in thousands. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

A.3 Import Competition from Other Countries

Since import competition from other countries might also affect students' choice of college major in the US and the influence might be differential, I use the import data of other countries to explore their impacts on American students' willingness to choose the six engineering majors. In this subsection, I classify countries into four groups (low, lower-middle, upper-middle, and high income) according to a country's gross national income (GNI) per capita in the year of 2000.[4] China belonged to the lower-middle income group in 2000. Here, I do not report the result of the low income group. There are 51, 60, and 53 countries for the lower-middle, upper-middle, and high income groups, respectively. Table A.3 shows the results of the three different income level groups. Columns 1-2 suggest that the import competition from the lower-middle income group has a negative effect on students' choice of the six engineering majors, and the magnitudes of the estimated coefficients are slightly smaller than their counterparts in Table 1.5. Nevertheless, when I switch my attention to the upper-middle income group, the results become statistically insignificant. Columns 5-6 show the results of high income countries. The influence from high income countries

[4] A country belongs to the low income group if its GNI per capita in 2000 was below $755. A country belongs to the lower-middle income group if its GNI per capita in 2000 was between $755 and $2994. A country belongs to the upper-middle income group if its GNI per capita in 2000 was between $2995 and $9265. A country belongs to the high income group if its GNI per capita in 2000 was over $9266.

is also not obvious, and the result in column 5 is barely significant at 10%.

Table A.3: Import Competition from Other Countries by Income Levels.

	Lower-middle income		Upper-middle income		High income	
	(1)	(2)	(3)	(4)	(5)	(6)
IMP weighted by migration	−0.0211***		−0.0119		−0.0053*	
	(−2.95)		(−1.39)		(−1.70)	
IMP weighted by migration and workplace		−0.0256**		−0.0143		−0.0057
		(−2.36)		(−1.18)		(−1.46)

Notes: Standard errors are robust to heteroskedasticity and clustered on the state of birth. t-statistics are in parentheses. State of birth, state of work, year fixed effects, and additional controls and fixed effects in Table 1.5 are included in each column. The number of observations is 182,461. All imports data are in 2007 US$ and values are in thousands. ***, **, * show significance at the 1%, 5%, and 10% levels, respectively.

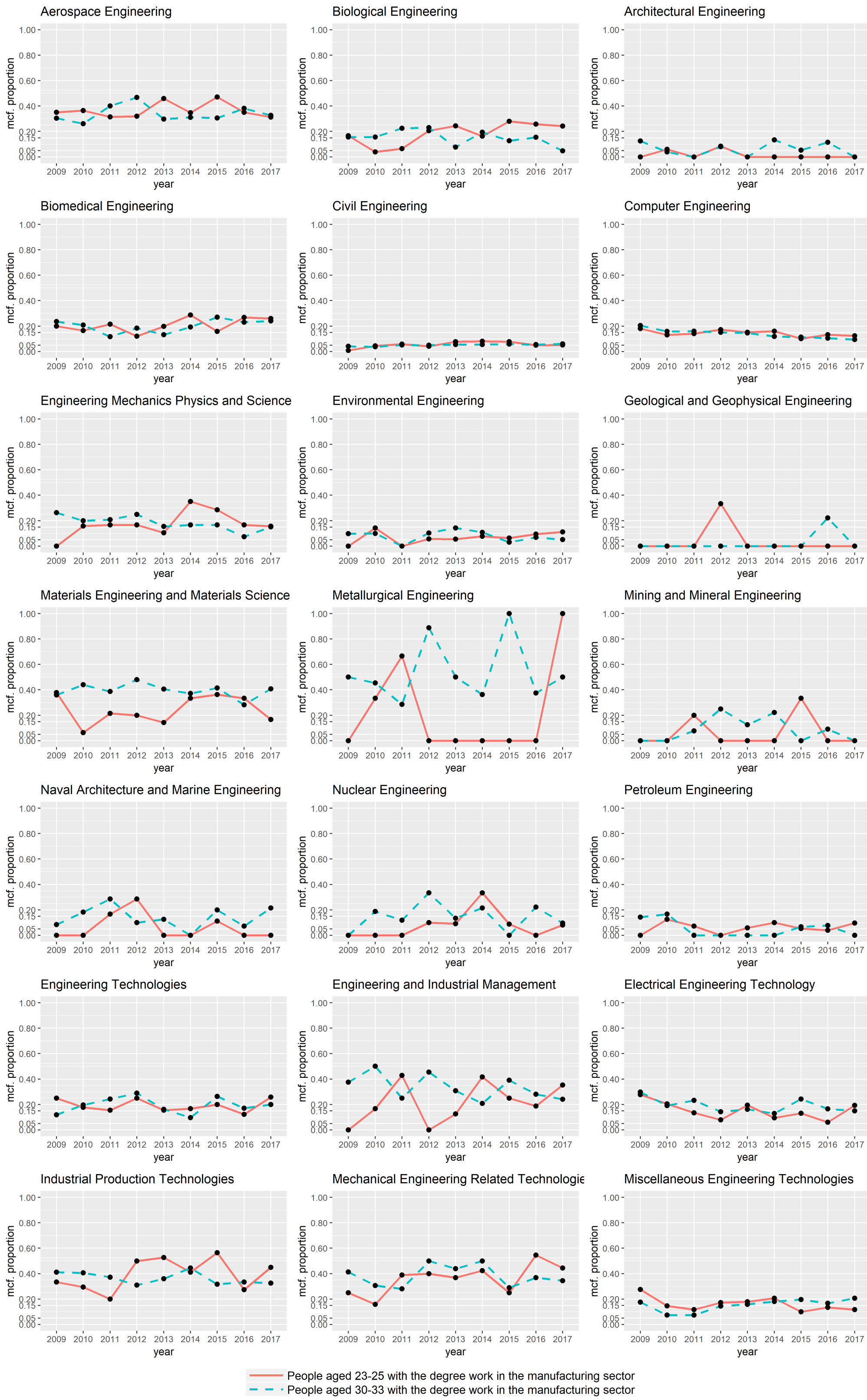

Figure A.1: Proportions of Other Engineering Majors in Manufacturing Industries.

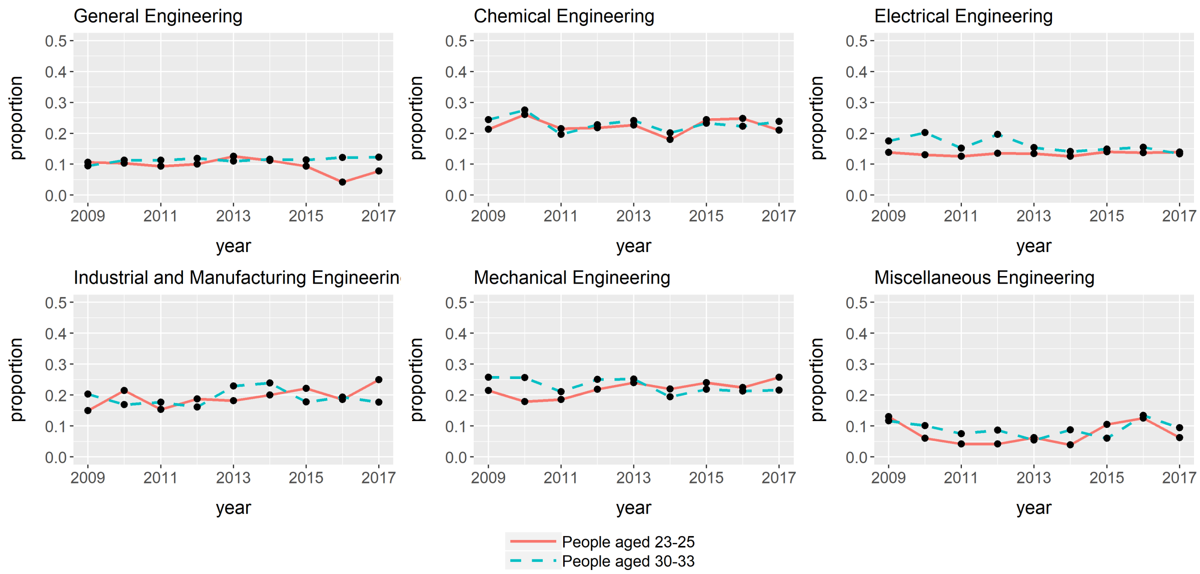

Figure A.2: Proportions of the Six Engineering Majors in the Selected Industries

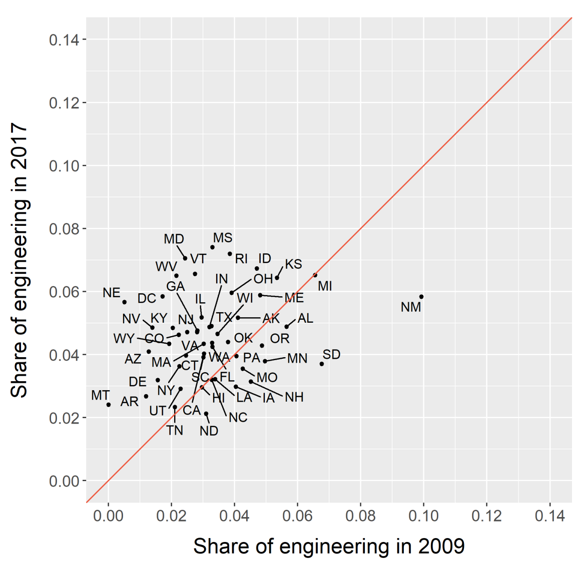

Figure A.3: Proportions of the Six Selected Engineering Majors in Each State between PUMS 2009 and 2017.

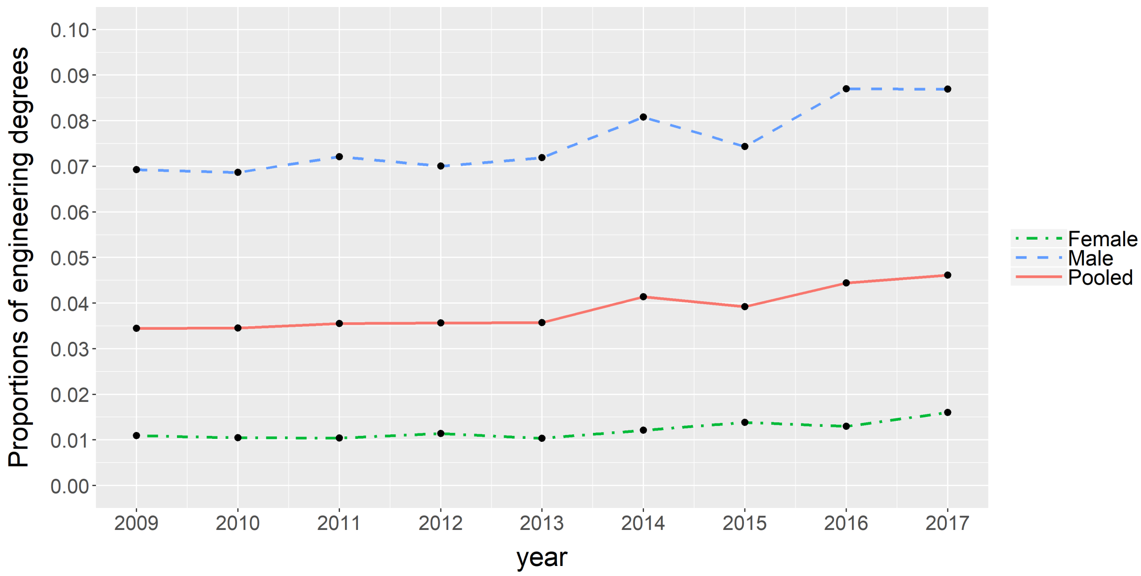

Figure A.4: Proportions of the Six Selected Engineering Majors from PUMS 2009 through 2017.

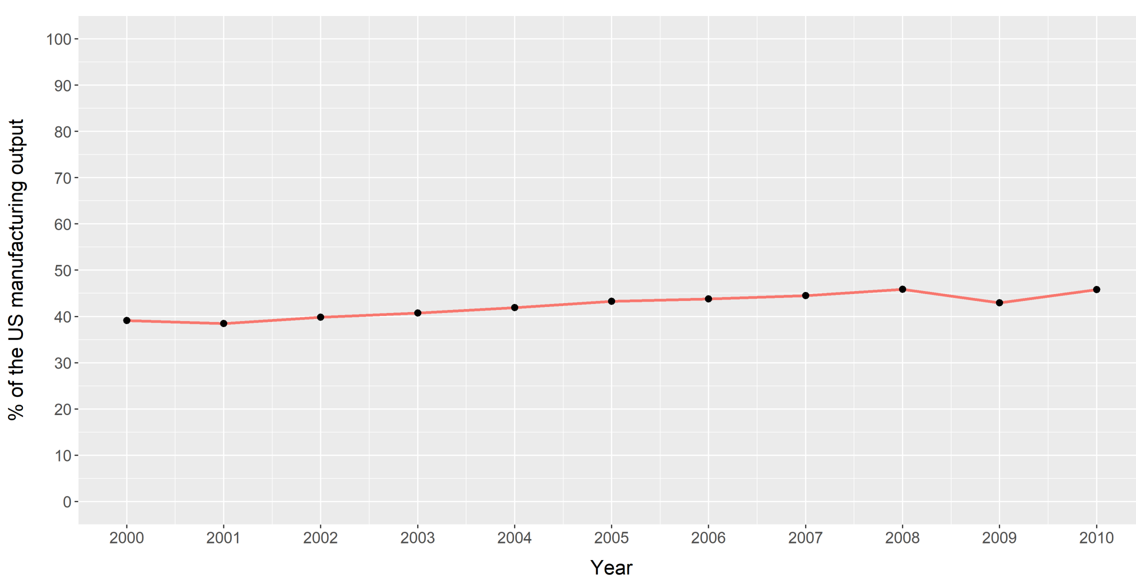

Figure A.5: Selected Manufacturing Industries' Output throughout the 2000s.

APPENDIX B

APPENDIX TO CHAPTER TWO

B.1 Supply-Driven Imports

To derive the supply-driven share of imports from low-income countries, I use the following decomposition of the OLS coefficient, from which I refer back to the appendix in Autor, Dorn, and G. Hanson (2013).

$$\hat{\beta}_{OLS} = \hat{\beta}_{2SLS}\frac{V(\mathrm{IMP}_{iv})}{V(\mathrm{IMP}_{iv}) + V(\mathrm{IMP}_{\hat{u}})} + \hat{\beta}_{\hat{u}}\frac{V(\mathrm{IMP}_{\hat{u}})}{V(\mathrm{IMP}_{iv}) + V(\mathrm{IMP}_{\hat{u}})}. \tag{B.1}$$

Equation B.1 presents that the OLS coefficient $\hat{\beta}_{OLS}$ can be written as a weighted average between the 2SLS coefficient $\hat{\beta}_{2SLS}$ and the residual coefficient $\hat{\beta}_{\hat{u}}$. $V(\mathrm{IMP}_{iv})$ is the variance of fitted imports from the instrumental variable, and $V(\mathrm{IMP}_{\hat{u}})$ is the variance of imports left out by the instrument. The three coefficients are derived by using the baseline equation as follows.

$$Outcomes_{s,t} = \ \alpha + \beta\mathrm{IMP}_{s,t^-} + T \times \phi_s + \varepsilon_{i,s,t}. \tag{B.2}$$

The labor market outcomes $Outcomes_{s,t}$ are state-level variables and include log weekly wages, the share of full-time jobs, the unemployment rate in state s, and in year t. IMP_{s,t^-} is the measure of trade exposure introduced in 2.4.1. $T \times \phi_s$ is the state linear time trend. Equation B.2 is evaluated by using the fixed-effects estimation to control for any time-invariant factors. With log weekly wages, I obtain $\hat{\beta}_{OLS} = -0.0258$, $\hat{\beta}_{2SLS} = -0.0797$, and $\hat{\beta}_{\hat{u}} = -0.0021$. With the share of full-time jobs, I have $\hat{\beta}_{OLS} = -0.0086$, $\hat{\beta}_{2SLS} = -0.1052$, and $\hat{\beta}_{\hat{u}} = 0.0256$. With the unemployment rate, I have $\hat{\beta}_{OLS} = 0.0039$, $\hat{\beta}_{2SLS} = 0.0681$, and $\hat{\beta}_{\hat{u}} = -0.0185$. Accordingly, $V(\mathrm{IMP}_{iv})/V(\mathrm{IMP}_{iv}) + V(\mathrm{IMP}_{\hat{u}}) \approx 0.305$, 0.262, and 0.259 for the three labor market outcomes. I use the average of the three values, implying the supply-driven component of imports from low-income countries is 0.275. This means the effect of trade exposure on students' choice on STEM majors is $0.275 \times \Delta\text{IMP} \times \hat{\beta}_{2SLS}$.

B.2 Beliefs About Labor Market Outcomes

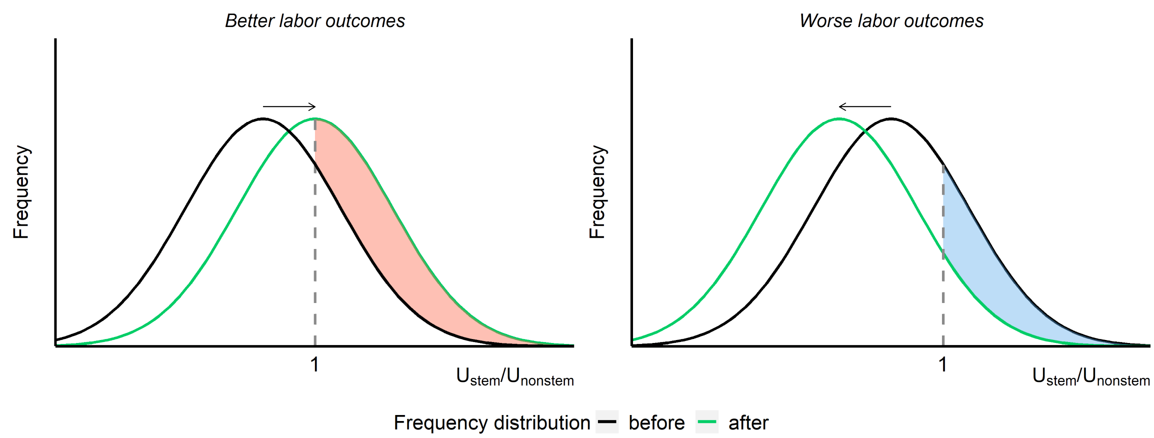

Figure B.1: Frequency Distribution Before and After Increased Trade Exposure

Notes: The green and black curves in the figure represent the frequency distribution before and after experiencing a rise in trade exposure,respectively. The left and right panels, respectively, show the better and worse labor market outcomes of STEM majors.

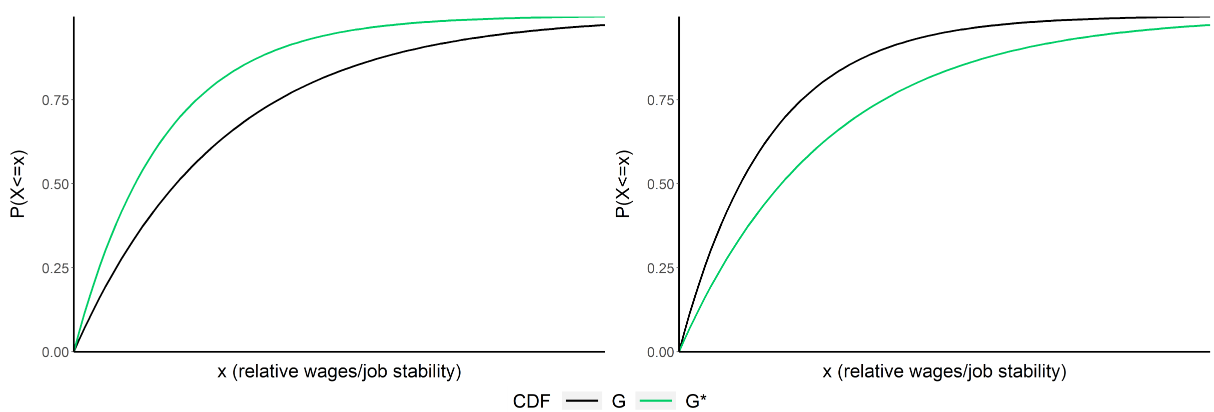

Figure B.2: Beliefs About the Distribution of Labor Market Outcomes (Relative Wages/Job Stability)

Note: The black and green curves in the figure represent students' beliefs about the distribution of labor market outcomes before and after accounting for increased trade exposure,respectively.

B.3 STEM Majors and Occupations

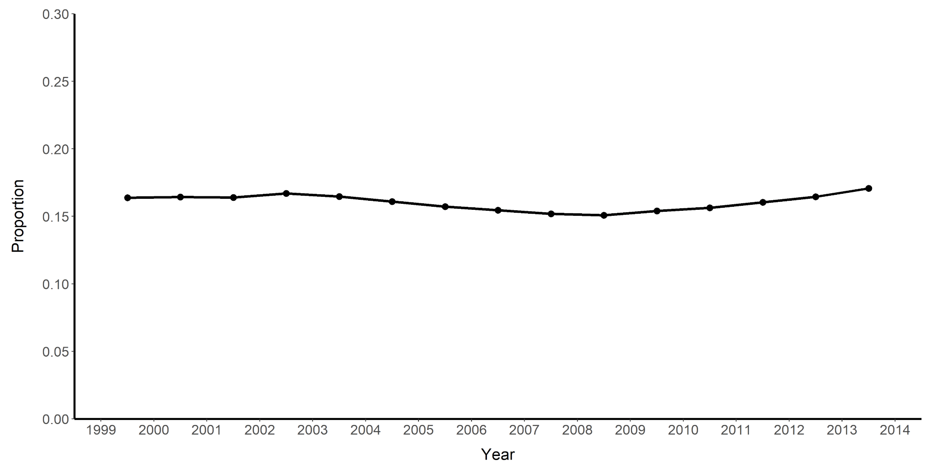

Figure B.3: Proportion of Bachelor's Degrees in STEM Fields

Notes: The data are taken from NCES. Each data point represents the proportion for an academic year (fall and spring semesters).

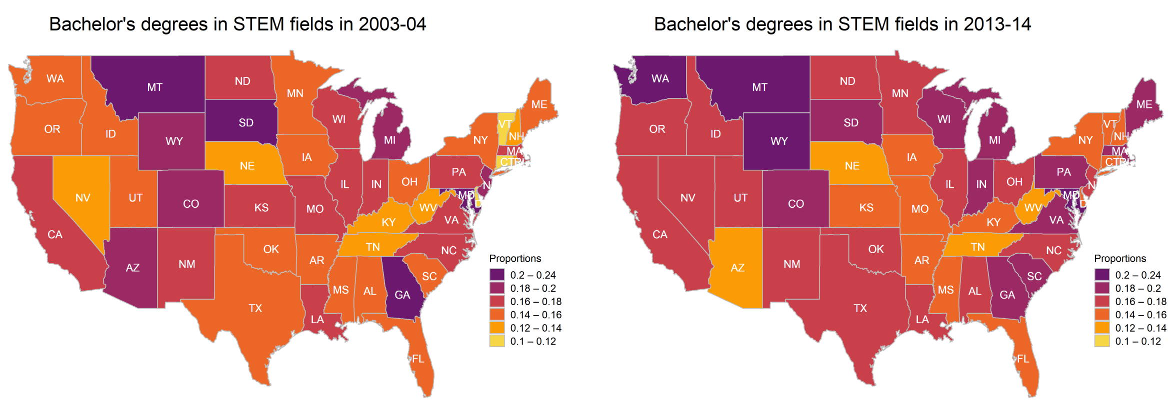

Figure B.4: Geographic Distribution of Bachelor's Degrees in STEM Fields Awarded in 2003-04 and 2013-14

Notes: The data are taken from NCES. Bachelor's degrees awarded in 2003-04 and 2013-14 roughly represent students' choice of major around 2000 and 2010.

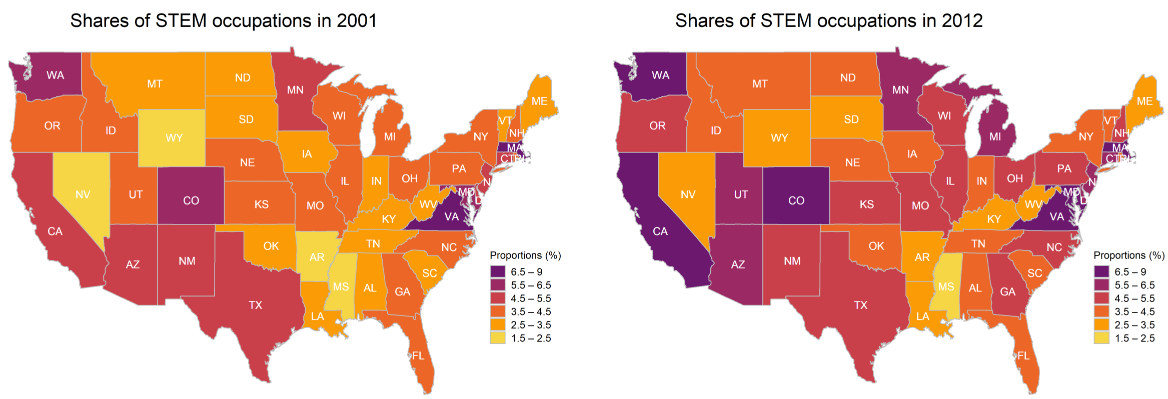

Figure B.5: Geographic Distribution of STEM Occupations in 2001 and 2012

Notes: The data are taken from the Occupational Employment Statistics (OES). For the list of STEM occupations, please refer to Table B.1.

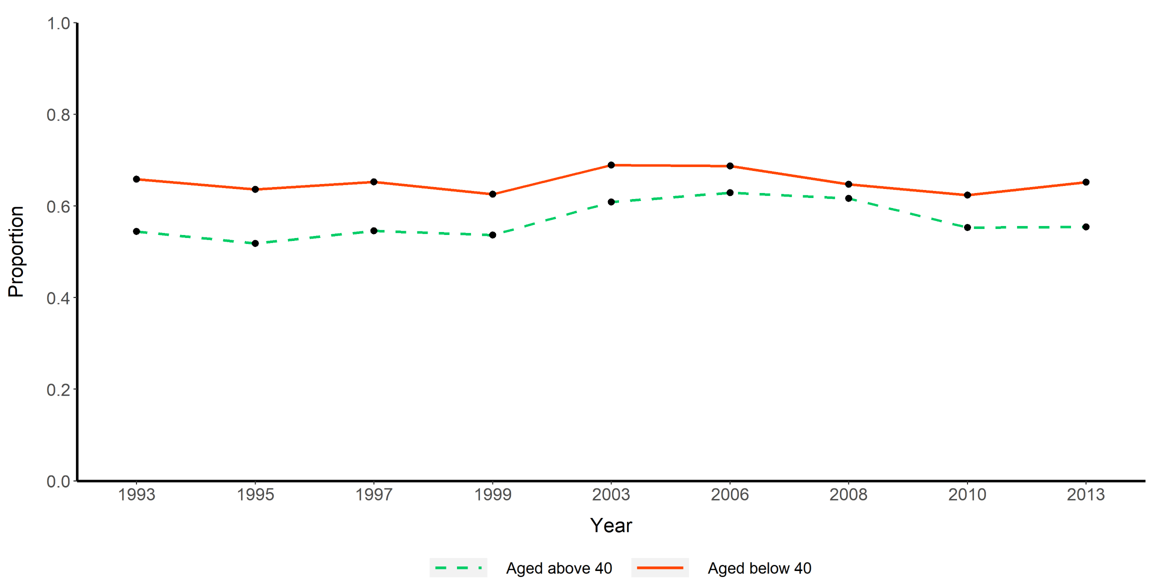

Figure B.6: Proportions of STEM Majors in STEM Occupations

Note: The data are taken from the nine waves of National Survey of College Graduates (NSCG).

Table B.1: List of STEM Occupations

ACS codes	Occupation title(s)
110	Computer and information systems managers
300	Architectural and engineering managers
360	Natural science managers
1000, 1110, 1040	Computer and information research scientists; Computer systems analysts; Computer occupations, all others; Computer network architects; Information security analysts; Web developers
1010	Computer programmers
1020	Software developers, applications, and systems software
1060	Database Administrators
1100	Network and Computer Systems Administrators
1200	Actuaries
1220	Operations Research Analysts
1210, 1230, 1240	Miscellaneous mathematical science occupations, including mathematicians and statisticians
1300	Architects, Except Naval
1310	Surveyors, Cartographers, and Photogrammetrists
1320	Aerospace Engineers
1330, 1340	Biomedical and Agricultural engineers
1350	Chemical Engineers
1360	Civil Engineers
1400	Computer Hardware Engineers
1410	Electrical and Electronics Engineers
1420	Environmental Engineers
1430	Industrial Engineers, including Health and Safety
1440	Marine Engineers and Naval Architects
1450	Materials Engineers
1460	Mechanical Engineers
1500	Petroleum, Mining and Geological Engineers, including Mining Safety Engineers
1510, 1520	Miscellaneous Engineeers including Nuclear Engineers
1540	Drafters
1550	Engineering Technicians, Except Drafters
1560	Surveying and Mapping Technicians
1600	Agricultural and Food Scientists
1610	Biological Scientists
1650	Medical Scientists, and Life Scientists, All Others
1700	Astronomers and Physicists
1710	Atmospheric and Space Scientists
1720	Chemists and Materials Scientists
1740	Environmental Scientists and Geoscientists
1760	Physical Scientists, All Other
1900	Agricultural and Food Science Technicians
1910	Biological Technicians
1920	Chemical Technicians
1940	Nuclear Technicians

Table B.2: Shares in the Fields of Education by Gender

	Males		Females	
Categories (%)	NLSY97-Under	NLSY97-Upper	NLSY97-Under	NLSY97-Upper
STEM	28.9	26.6	12.1	10.0
Biological sci.	2.8	2.4	5.1	4.1
Computer sci.	12.4	10.8	3.6	2.8
Engineering	10.0	8.7	1.3	1.1
Mathematics	1.1	1.2	0.7	0.7
Technology/other sci.	2.6	3.5	1.4	1.3
Business	21.0	21.1	16.1	17.4
Health care	5.6	5.4	21.7	19.8
Social science	11.6	13.2	14.9	15.5
Education	4.0	3.6	10.8	11.3
Humanities	11.9	13.7	11.7	12.7
Others	17.0	16.4	12.7	13.3

Notes: The sample comes from NLSY97. "Under" and "Upper" refer to choices of major for college underclassmen and upperclassmen.

Table B.3: Proportions of Each Field in STEM Occupations by Age

Categories (%)	23-30	31-40	41-50	51-60
STEM	65.0	60.7	60.5	61.3
Business	10.2	13.1	15.1	14.1
Health professions	1.2	1.2	1.4	1.8
Social sciences	9.0	9.4	8.6	7.4
Education	0.9	1.4	1.7	3.1
Humanities	5.7	6.5	5.8	5.2
Others	8.0	7.8	6.9	7.1

Note: The sample comes from ACS 2009-2017.

B.4 Trade Exposure

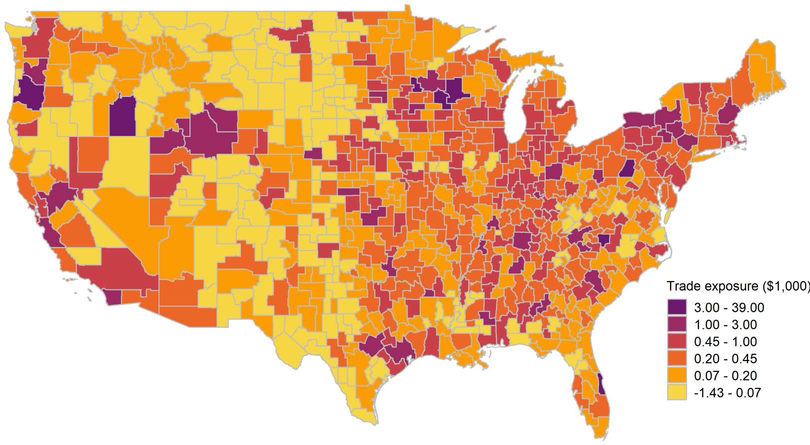

Figure B.7: Geographical Distribution of Trade Exposure at the Commuting Zone Level (Specific to STEM Occupations)

Notes: The map shows the difference of trade exposure between 2000 and 2010. The values are in thousands of US$.

B.5 Alternative Specifications

Table B.4: Different Time Lagged Measures of Import Competition

	Underclassmen			Upperclassmen		
	(1)	(2)	(3)	(4)	(5)	(6)
1-year lagged IMP	0.0663^{**}			0.0383^{***}		
	(0.029)			(0.014)		
2-year lagged IMP		0.0800^{*}			0.0687^{***}	
		(0.042)			(0.025)	
3-year lagged IMP			0.0656			0.0473^{**}
			(0.044)			(0.022)

Notes: Standard errors in parentheses are robust to heteroskedasticity and clustered on the c-zone. C-zone linear time trend, c-zone 1997 fixed effect, and cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

Table B.5: Alternative Specifications

	Linear prob. model		Probit	
	Under (1)	Upper (2)	Under (3)	Upper (4)
(Imports from *low income* to U.S.)/worker (IMP)	0.0557^{*} (0.033)	0.0428^{***} (0.014)	0.1926 (0.267)	0.5856^{**} (0.290)
Average partial effects			0.0464	0.0607
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	5,495	5,495	5,215	5,164

Notes: “Under" and “Upper" refer to choices of major for college underclassmen and upperclassmen. The choice of major in the first part of college is included as a control in columns 2 and 4. Standard errors in the parentheses of columns 1 and 2 are robust to heteroskedasticity and clustered on the c-zone. Bootstrapped standard errors are in the parentheses of columns 3 and 4. Year fixed effects, c-zone 1997 fixed effect, and cohort fixed effects are included in each column. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

B.6 Dissection of STEM Majors

Table B.6: 2SLS Estimates of Engineering and Non-Engineering Majors

	Underclassmen		Upperclassmen	
	Engineering (1)	Non-engineering (2)	Engineering (3)	Non-engineering (4)
A. NLSY97				
(Imports from *low income* to U.S.)/worker	0.0665**	0.0186	0.0623***	−0.0038
	(2.50)	(0.55)	(2.68)	(−0.13)
B. ACS				
(Imports from *low income* to U.S.)/worker			0.0352***	0.0864***
			(4.90)	(5.89)

Notes: The first-part choice of major is included as a control in the specifications of columns 3-4 in panel A. Standard errors are robust to heteroskedasticity and clustered on the c-zone in each column of panel A. C-zone linear time trend, c-zone 1997 fixed effect, and cohort fixed effects are included in each column of panel A. Standard errors are robust to heteroskedasticity and clustered on state of birth for specifications in panel B. State linear time trend and state of birth fixed effect are included in each column of panel B. t-statistics are in parentheses. All imports data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

B.7 Wage Differential

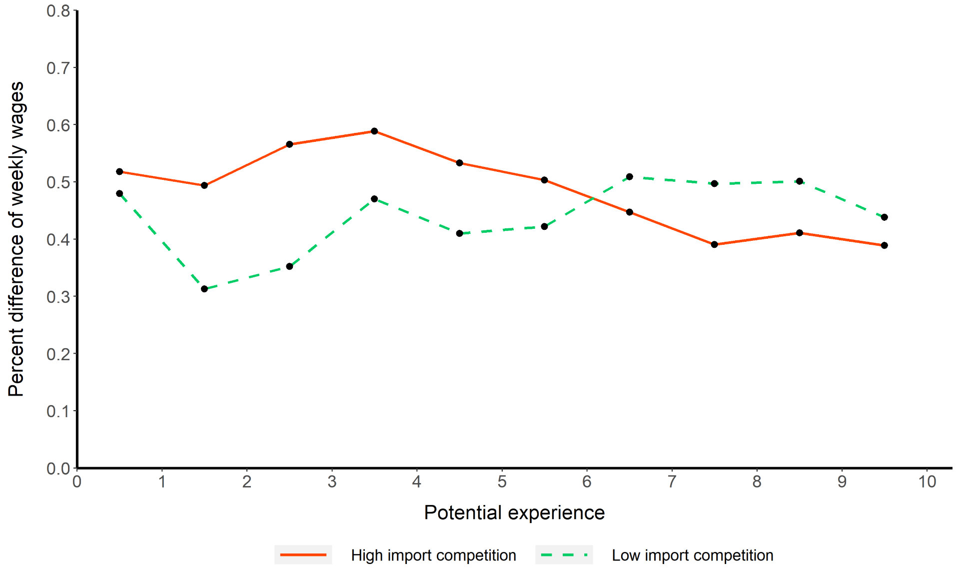

Figure B.8: Wage Differential Between STEM and Non-STEM Occupations

Notes: Potential experience is defined as the number of years after graduation from the first college. Each data point is derived by using the average of two wage differentials and therefore does not correspond to an integer value of potential experience. For example, the wage differential that corresponds to 1.5 years of potential experience is the average value of wage differentials for people with 1 and 2 years of potential experience. The data are from NLSY97. Respondents in NLSY97 are assigned to "high (low) import competition" if import competition faced by their c-zones is higher (lower) than the median value of import competition. The observations with the top and bottom 1% of weekly wages are dropped in case of bias from extreme values.

APPENDIX C

APPENDIX TO CHAPTER THREE

Table C.1: Fields of Education and Matched Occupations

Fields of education	Occupation titles
Agriculture/Environment and Natural Resources	0205 Farmers, Ranchers, and Other Agricultural Managers 0360 Natural Science Managers 0510 Buyers and Purchasing Agents, Farm Products 1600 Agricultural and Food Scientists 1610 Biological Scientists 1640 Conservation Scientists and Foresters 1740 Environmental Scientists and Geoscientists 1900 Agricultural and Food Science Technicians 1910 Biological Technicians 3250 Veterinarians 6005 First-Line Supervisors of Farming, Fishing, and Forestry Workers 6050 Agricultural Workers, nec (not elsewhere classified) 6120 Forest and Conservation Workers
Biology and Life Sciences	0350 Medical and Health Services Managers 0360 Natural Science Managers 1610 Biological Scientists 1910 Biological Technicians 1960 Life, Physical, and Social Science Technicians, nec 3000-3650 Healthcare Practitioners and Technical Professions
Business	0010-0950 Management, Business, and Financial Specialists 4700-4965 Sale Related Professions
Communication	0030 Managers in Marketing, Advertising, and Public Relations 2810 Editors, News Analysts, Reporters, and Correspondents 2825 Public Relations Specialists 2850 Writers and Authors 2860 Media and Communication Workers, nec 2900 Broadcast and Sound Engineering Technicians and Radio Operators, and Media and Communication Equipment Workers, all others 2920 Television, Video, and Motion Picture Camera Operators and Editors 4800 Advertising Sales Agents 5030 Communications Equipment Operators, all others
Computer and Information Sciences	0110 Computer and Information Systems Managers 1000-1100 Computer and Mathematical Professions 5800 Computer Operators 7900 Computer Control Programmers and Operators
Education Administration and Teaching	0230 Education Administrators 2200-2550 Education, Training, and Library

Table C.2: Fields of Education and Matched Occupations (cont'd)

Fields of education	Occupation titles
Architecture/Engineering	0300 Architectural and Engineering Managers 1000 Computer Scientists and Systems Analysts/Network systems Analysts/Web Developers 1020 Software Developers, Applications and Systems Software 1300 Architects, except Naval 1320-1550 Architecture and Engineering Professions 9030 Aircraft Pilots and Flight Engineers
Medical and Health Sciences and Services	0350 Medical and Health Services Managers 3000-3650 Healthcare Practitioners and Technical Professions
History	2200-2550 Education, Training, and Library
English Language and Literature/Foreign Languages	0230 Education Administrators 2200-2550 Education, Training, and Library Professions 2810 Editors, News Analysts, Reporters, and Correspondents 2840 Technical Writers 2850 Writers and Authors
Law	2100-2150 Legal Professions
Mathematics and Statistics	0110 Computer and Information Systems Managers 1000-1100 Computer and Mathematical Professions 1200 Actuaries 1230 Statisticians 1240 Mathematical Science Occupations, nec
Physical Sciences/Nuclear, Industrial Radiology, and Biological Technologies	0360 Natural Science Managers 1700 Astronomers and Physicists 1710 Atmospheric and Space Scientists 1720 Chemists and Materials Scientists 1740 Environmental Scientists and Geoscientists 1760 Physical Scientists, nec 1920 Chemical Technicians 1930 Geological and Petroleum Technicians, and Nuclear Technicians 1960 Life, Physical, and Social Science Technicians, nec
Psychology	1820 Psychologists 2000 Counselors 2010 Social Workers
Philosophy and Religious Studies/Theology and Religious Vocations	2040 Clergy 2050 Directors, Religious Activities and Education 2060 Religious Workers, nec
Social Sciences	0010 Chief executives and legislators/public administration 0500-0950 Business Operations Specialists 1800 Economists and Market Researchers 1830 Urban and Regional Planners 1840 Social Scientists, nec 1960 Life, Physical, and Social Science Technicians, nec 2100-2150 Legal Professions

Note: Occupation coding follows the Census Bureau's 2010 ACS occupation classification scheme.

Table C.3: Impact of Import Competition on the Supply of College Graduates - CPUMA level

	All		Males		Females	
	Coeffs. (1)	S.E. (2)	Coeffs. (3)	S.E. (4)	Coeffs. (5)	S.E. (6)
All fields	0.017	0.012	0.015*	0.009	0.022	0.016
Field of education:						
Agriculture/natural resources	0.069***	0.021	0.051	0.035	0.115**	0.047
Biology and life sciences	0.050**	0.024	0.138***	0.029	0.009	0.025
Business	−0.042***	0.015	−0.033*	0.017	−0.055***	0.018
Communication	0.038*	0.020	0.064**	0.030	0.031	0.025
Computer and info. sciences	0.023	0.024	0.027	0.024	−0.019	0.040
Education	−0.002	0.028	0.033	0.032	−0.011	0.029
Engineering	0.020	0.025	0.023	0.022	−0.080***	0.029
Health professions	0.117**	0.051	0.103**	0.049	0.126***	0.043
History	0.096***	0.032	0.131***	0.030	0.093***	0.034
English/foreign languages	0.107***	0.032	0.117***	0.033	0.096***	0.036
Law	0.220**	0.103	0.152	0.117	0.160	0.103
Math and statistics	0.093***	0.026	0.049	0.032	0.160***	0.047
Physics/nuclear tech.	0.117***	0.025	0.148***	0.030	0.016	0.029
Psychology	0.108***	0.021	0.186***	0.032	0.107***	0.021
Philosophy and religion	0.080**	0.035	0.068*	0.037	0.053	0.041
Social sciences	−0.004	0.018	0.035	0.028	−0.008	0.017

Notes: Standard errors (S.E.) are robust to heteroskedasticity and clustered on CPUMA. CPUMA-specific linear time trend, CPUMA, occupation, industry, and age cohort fixed effects are included. When the sample includes all fields of education, respondents' first and second fields of education are included in the specification as controls. All import data are in 2007 US$, and values are in thousands. ***, **, and * show significance at the 1%, 5%, and 10% levels, respectively.

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