Human Capital Development under Trade Conflict

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Abstract

This paper studies the impact of China-US trade war on human capital development in China, as captured by college major choice. We conduct both theoretical and empirical analyses. The simple model indicates that information signaling better prospects for STEM graduates can push high ability students toward STEM majors. Our empirical investigation leverages novel, detailed data on college admission statistics. We document an increased gap in admission cutoffs between STEM and non-STEM majors after the trade war broke out in 2018, implying a shift of high ability students toward STEM majors. This increase in the cutoff gap is more pronounced in provinces highly exposed to additional US tariffs. We offer evidence that the behavioral change in major choice is due to career considerations based on observed advantages of STEM graduates or attention to STEM-favorable national development plans, rather than nationalistic responses to the nation's call for tech self-sufficiency.

Keywords: China-US trade war; human capital; major choice; industrial policy; nationalism.
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1 Introduction

Human capital refers to the knowledge, skills, abilities, and attributes individuals acquire through education, training, and experience (Becker, 1964). It plays a crucial role in economic development (see, among others, Lucas, 1988). Among various avenues of human capital accumulation within a country, particularly important is higher education (Acemoglu and Autor, 2011). It offers individuals opportunities to acquire advanced knowledge, specialized skills, and critical thinking abilities, thereby enhancing labor productivity (Hanushek and Woessmann, 2012), which, in turn, contributes to economic growth (Barro and Lee, 2013).

As the starting point of higher education, major choice is a prominent factor in shaping the composition and structure of a country's human capital. Existing literature has underscored the implications of schooling for the development of specific skills and knowledge within the labor force, suggesting that the selection of college majors can also play a crucial role in skill formation (Carneiro and Heckman, 2003; Oreopoulos and Salvanes, 2011). When choosing a major, multiple factors come into play, including personal interests, aptitudes, career goals, societal expectations, family influence, academic performance, financial considerations, and future job prospects (Altonji et al., 2012, 2016; Wiswall and Zafar, 2016). A large body of studies has emerged to understand the role of these factors through the lens of variation in socioeconomic environments, such as business cycles and technological change, and institutions (e.g., Ersoy, 2020; Blom et al., 2021; Weinstein, 2022; Ebeke et al., 2015).

However, little is known about the impact of trade conflict with partner countries on domestic major choice and human capital development. There are several reasons to expect that trade conflict can lead to a significant, distinctive impact on a country's human capital development, which merits in-depth investigations. On the one hand, fluctuating trade relations introduce uncertainty to the economy and thus affect people's expectations regarding industrial development. Students and their families may take into account this uncertainty when choosing college majors, as they consider the potential impacts of trade dynamics on industry demand and job prospects (Qiu et al., 2019; Fajgelbaum et al., 2020; Fajgelbaum and Khandelwal, 2021; Jiao et al., 2022).

On the other hand, unlike conventional economic downturns, trade conflict may prompt the government to adjust industrial policies, creating incentives for students to pursue majors favored by national plans of industrial development. Specifically, government support may be placed on certain sectors or industries, typically high-tech, to enhance their competitiveness and to sustain overall growth potentials, which can generate heightened demand and favorable prospects for professionals with relevant skills. As such, individuals may be incentivized or guided toward choosing majors that align with national objectives. For example, a country aspiring to advance its renewable energy industry would have a high demand for graduates of majors related to sustainable engineering, renewable energy technologies, or environmental sciences.

Additionally, trade conflict may stimulate nationalism. In relation to national development plans in response to trade conflict, the government and public opinion may attach patriotism to enrollment in certain majors and mobilize active participation in specific industries. For example, the US's chip ban on China has enhanced techno-nationalism within China, represented by consumer favoritism of products with self-developed chips and high respect for semiconductor firms (Zhang, 2022; BBC, 2019).

Inspired by these conjectures, this paper attempts to shed light on the impact of trade conflict on domestic major choice and human capital development. Our investigation is built upon the China-US trade war since 2018, one of the biggest trade conflict episodes in recent history. The trade war unfolded on March 22, 2018, with the release of the "Section 301 Fact Sheet" that accused China of unfair economic practices.[1] Subsequently, the US imposed five waves of extra tariffs on Chinese products in 2018 and 2019.[2] Notably, the tariffs particularly targeted the products of high-tech sectors included in China's distorting industrial policy "Made in China 2015" Project (Ju et al., 2024). Amidst the trade war, on April 16, 2018, the US imposed sanctions on the Chinese firm, Zhongxing Telecommunication Equipment (ZTE) Corporation, barring it from purchasing parts from American companies. This incident raised widespread concerns within China about the self-sufficiency of key technologies, especially semiconductor manufacturing (e.g., The Hill, 2018; Yang and Hornby, 2018).

We focus on how the trade war, characterized by salient trade tensions and economic uncertainties, influenced Chinese students' decisions on their college majors, especially the Science, Technology, Engineering, and Mathematics (STEM) majors, which are related to vulnerable sectors in the trade war. To start with, we present a simple theoretical model to clarify the pathways through which the trade war may influence major choices. The results suggest that information signaling better prospects for STEM graduates can push high-ability students toward STEM majors. The trade war can affect major choices by

[1]See https://ustr.gov/about-us/policy-offices/press-office/fact-sheets/2018/march/section-301-fact-sheet.

[2]More details about these tariffs are discussed in Section 5 when we use them in empirical analysis.

influencing decisive information through three aforementioned channels: labor market performance, attention to industrial policy, and nationalistic sentiments.

Our empirical analysis utilizes a unique, granular dataset of college admission results. Employing a difference-in-differences (DID) approach, we document that after 2018, i.e., after the China-US trade war unfolded, there was a significant increase in the admission cutoff of STEM majors relative to that of non-STEM majors, implying that high-ability students sort into STEM majors. The trade war likely plays a distinctive role: there is no strong evidence for preexisting divergent patterns of the two types of majors leading up to 2018. Through a simulation exercise, we confirm that the finding is not likely produced by an idiosyncratic shock that mechanically moves admission cutoffs of the two types of majors in opposite directions in equilibrium.

We further illuminate the trade war's role and the relevant mechanisms underlying the shift in major choice. Exploiting regional variation in exposure to additional US tariffs, we show that high-exposure provinces witnessed a more pronounced shift toward STEM majors, highlighting the importance of the direct, localized experience of the trade war despite its nationwide salience. In light of our theoretical prediction that information positively correlated with the expected returns of STEM graduates can prompt students to pursue STEM disciplines, we provide evidence of how the trade war intervened in information relevant to major choice. We show that the STEM majors exhibited more resilient labor market performance during the trade war, as captured by wages. We also find that the trade war increased public attention to China's high-tech-oriented industrial policy. In contrast, we do not find strong evidence that the size of the trade war's impact on major choice is related to nationalistic sentiments. Taken together, these results corroborate that when selecting STEM majors, students are primarily motivated by the relatively higher wages of STEM fields and the nation's industrial policy, both of which relate to material returns, rather than by the influence of rising nationalism in Chinese society following the trade war.

Our paper makes several contributions to the existing literature. Firstly, our research joins the large literature on human capital development, especially in response to globalization. Existing research mainly focuses on labor skill formation and educational attainment. For example, Falvey et al. (2010) propose a theory of trade liberalization and human capital adjustment, suggesting that trade liberalization in a relatively skilled labor abundant country may induce younger and more unskilled workers to upgrade their skills via schooling. Similarly, Blanchard and Willmann (2016) argue that human capital responses to globalization may be non-monotonic, with heterogeneous workers acquiring more or fewer skills in response to changes in the wage structure. Auer (2015) theoretically examines the cross-country income and welfare consequences of trade-induced human capital (dis-)accumulation. There is also extensive empirical evidence from various contexts. Edmonds et al. (2010) find that India's removal of tariff protection causes a relative rise in poverty and thus makes families reduce schooling to save schooling costs. Atkin (2016) shows that the growth of less-skilled export manufacturing in Mexico, which raised the opportunity cost of schooling, increased school dropout. Lin and Long (2020) show that while export expansion reduced high school attendance, it encouraged more high school graduates to pursue higher education in China. Despite these rich insights into the impacts of globalization on educational attainment, relatively little attention has been paid to college major choices, an important channel of human capital development. Our study provides new evidence in this specific area. The novelty of our paper also derives from its focus on trade conflict, as opposed to regular trade liberalization.

Secondly, our paper adds to the trade literature, particularly the growing literature that evaluates the consequences of the trade war. Previous studies have predominantly focused on economic and political outcomes (see Fajgelbaum and Khandelwal (2021) for a review), such as trading patterns (Jiao et al., 2022; Nicita, 2019), global value chain (Mao and Görg, 2020; Handley et al., 2020; Bellora and Fontagné, 2020), trade policy uncertainty (Benguria et al., 2022), commodity price and consumer welfare (Waugh, 2019; Amiti et al., 2019, 2020; Carter and Steinbach, 2020; Flaaen et al., 2020; Fajgelbaum and Khandelwal, 2021), stock market (Burggraf et al., 2019; Egger and Zhu, 2019), labor market dynamics (He et al., 2021), entrepreneurship (Cui and Li, 2021; Yoon and Park, 2022; Xue et al., 2024), and electoral politics (Blanchard et al., 2024; Kleinman et al., 2020; Fetzer and Schwarz, 2021; Chyzh and Urbatsch, 2021; Kim and Margalit, 2021; Lake and Jun, 2023; Choi and Lim, 2023). Our paper provides a new perspective by examining the impact of the China-US trade conflict on major choices in China.

Finally, our paper relates to the studies on nationalism. There is a burgeoning literature that documents nationalism's linkage with economic openness and its impacts on economic exchange (Lan and Li, 2015; Colantone and Stanig, 2019; Gries et al., 2011; Fisman et al., 2014). We explore human capital development under rising nationalism during the trade conflicts. Our results suggest a limitation of nationalism in influencing high-stake educational decisions.

The rest of this paper is organized as follows. Section 2 provides a conceptual model that guides our empirical investigations. Section 3 describes our data. Sections 4 and 5 present our findings. Section 6 concludes.

2 A Conceptual Model

2.1 The Model

In this section, to provide guidance for subsequent empirical investigations, we present a simple conceptual framework that sketches how the trade war can influence college major choice.

Basic Settings. Suppose that at period t, a risk-neutral student i (as well as their family) needs to choose between two majors (or "super-programs"): STEM (S) vs. non-STEM (N). We assume that student i possesses a characteristic $a_i \in [0, \bar{a}]$, which can be interpreted as the skill that governs the payoff differential between two majors. In addition, we assume a student's performance in the college entrance exam is strictly increasing in a_i. In the population, a_i satisfies a uniform distribution over $[0, \bar{a}]$, and its c.d.f is denoted by F.[3] Without loss of generality, we suppose that there is a unit mass of students.

Major choice hinges on the expectation of future payoffs. At period $t+1$, student i who graduates with major $m \in \{S, N\}$ will obtain a payoff $y_{im,t+1}$. The differential in payoffs is expressed as:

$$\Delta y_{i,t+1} = y_{iS,t+1} - y_{iN,t+1} = u_{t+1} + m_{t+1} a_i. \tag{1}$$

In this expression, u_{t+1} is an idiosyncratic disturbance at period $t+1$, which satisfies a standard normal distribution $N(0,1)$.

m_{t+1} captures the extent to which the economic conditions at period $t+1$ are favorable for a STEM graduate with skill a_i. Importantly, m_{t+1} realizes at $t+1$, so its value is unknown to student i at t, when they decide on college majors. We assume that m_{t+1} satisfies a normal distribution $N(0,1)$, which, however, is known to students at t. Moreover, student i can use the information available at t, denoted by vector I_t, to form an expectation of m_{t+1} and then make major choice accordingly. I_t may involve knowledge about wages, labor demand, industrial policy, etc. For simplicity, we treat I_t as a composite or a reduced-form representation of all kinds of information relevant to major choice, and we assume that I_t satisfies a normal distribution $N(0,1)$. Without loss of generality, we assume that a higher level of I_t reflects more favorable current conditions for STEM graduates.[4]

How does I_t help with predicting m_{t+1}? Using the well-known formula for conditional

[3] The distributional assumptions made here and subsequently are for simplicity. None of the predictions rely on particular distributional assumptions.

[4] Realistically, there exists bad information. However, as conventional in economics, one can always redefine the bad information inversely so that it fits into our framework.

expectations of normal distributions, we can derive:

$$E\left[m_{t+1} \mid I_t\right] = rI_t, \tag{2}$$

where $r = Cov\left(m_{t+1}, I_t\right)\left[Var\left(I_t\right)\right]^{-1} = Cov\left(m_{t+1}, I_t\right)$. We suppose $r > 0$. That said, more favorable conditions for STEM graduates at period t (higher I_t) entail optimistic beliefs about the prospects of STEM graduates at period $t+1$ (higher expected m_{t+1}). Our primary interest in this model is how a change in I_t influences major choice, *ceteris paribus*.

Lastly, we assume there is a cost of enrolling in STEM majors as opposed to non-STEM majors, denoted by c. It could be interpreted as either a monetary cost (e.g., tuition) or a psychological cost (e.g., difficulty of study).

The Student's Problem. At period t, student i chooses a major based on available information to maximize their expected payoff, taking into account the cost. Therefore, they will make the STEM major the first choice when

$$E\left[\Delta y_{i,t+1} \mid I_t\right] \geq c, \tag{3}$$

that is, when the STEM major is expected to be more profitable based on current information. It is important to note that satisfying Equation 3 only means that an individual student *prefers* the STEM major over the non-STEM major; it does not mean that the student would be necessarily admitted into the STEM major. The admission results depend on all students' preferences and each major's admission quotas. We discuss this issue later.

Plugging in Equation 1, Equation 3 can be written as:

$$E\left[u_{t+1} \mid I_t\right] + E\left[m_{t+1} \mid I_t\right] a_i \geq c. \tag{4}$$

Recall that $u_{t+1} \sim N(0,1)$ is an idiosyncratic shock and so independent of I_{it}, thus, $E\left[u_{t+1} \mid I_t\right] = E\left[u_{t+1}\right] = 0$. Recall $E\left[m_{t+1} \mid I_t\right] = rI_t$. Taken together, we obtain the following condition under which student i prefers the STEM major:

$$\left(rI_t\right) a_i \geq c. \tag{5}$$

Equation 5 implies that the sorting between majors is contingent on current information I_t that governs expectations of STEM graduates' prospects.

- If I_t is high enough, $I_t \geq \hat{I}_t \equiv \frac{c}{r\bar{a}} > 0$, i.e., the current information projects a sufficiently optimistic future for STEM graduates, a set of students, denoted by *STEM*, who possess high abilities ($a_i > \frac{c}{rI_t}$) would make the STEM major their first choice. Then, the fraction of students preferring the STEM major is

$$p \equiv \Pr(STEM) = 1 - F\left(\frac{c}{rI_t}\right) = 1 - \frac{1}{\bar{a}}\frac{c}{rI_t}. \tag{6}$$

- By contrast, if I_t is low ($I_t < \hat{I}_t$), none of the students would make the STEM major their first choice. That said, $STEM = \emptyset$ and $p = 0$.

Figure 1 visualizes p as a function of I_t, which, as expected, shows that p is non-decreasing in I_t.

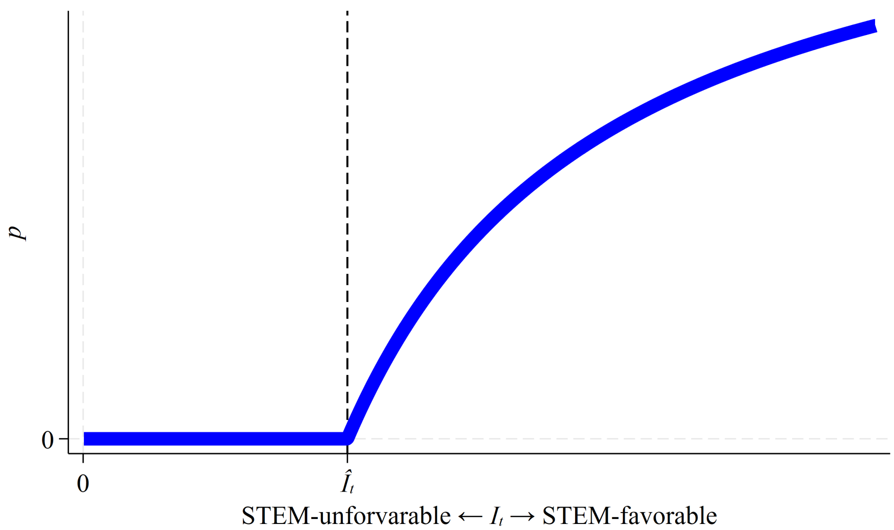

Figure 1: Fraction of Students Preferring the STEM Major

Observable Admission Results. Thus far, we consider an individual student's major choice problem. Now, we proceed to consider how the individual major choice translates into aggregate college admission results, which are *observable* to us and ready for empirical tests. To fix terminologies, we call students the demand side and colleges the supply side on the admission market.

When applying to college, a student is supposed to submit a list of majors in the order of their preferences. In our simple settings, the list is an ordering of the STEM and non-STEM majors. For students satisfying Equation 5, they would rank STEM major in the first place while the non-STEM major in the second, and *vice versa*. However, not everyone would be admitted by their most preferred major. The admission results depend on the distribution of students' preferences *and* each major's quotas. Suppose that the STEM major offers $q \in (0, 1)$ seats. Recall that we assume a unit mass of students, then q can also be interpreted as the fraction of students who can ultimately admitted by the STEM major. Thus, correspondingly, the non-STEM major offers $(1-q)$ seats. These quotas resolve excess demand or excess supply, thus equilibrating the admission market.

In the following, we focus on two objects: (i) the set of students ultimately admitted by the STEM major, denoted by $AdSTEM \subset [0, \bar{a}]$; (ii) these students' minimum skill (or equivalently, the minimum performance in college entrance exam), namely, $a^S_{\min} = \inf_a AdSTEM$. We can also define non-STEM counterparts: (i) $AdNonSTEM = [0, \bar{a}] \setminus AdSTEM$ and (ii) $a^N_{\min} = \inf_a AdNonSTEM$. As we will describe in Section 3, $a_{\min}$'s are directly observed as admission cutoffs, the minimum scores required for getting admitted.

Now, we characterize admission results in different scenarios for the demand-supply relationship in the admission market.

- If $p \geq q$, students have *excess demand* for the STEM major. This occurs when $I_t \geq \frac{c}{(1-q)r\bar{a}} \equiv \tilde{I}_t$, i.e., when I_t is sufficiently optimistic about STEM graduates' prospects. Note also $\tilde{I}_t > \hat{I}_t$. In this scenario, only the top q fraction of students in the skill distribution can get into the STEM major. Therefore,

$$AdSTEM = \left[F^{-1}(1-q), \bar{a}\right] = [(1-q)\bar{a}, \bar{a}], \tag{7}$$

$$AdNonSTEM = [0, (1-q)\bar{a}), \tag{8}$$

$$a^S_{\min} = (1-q)\,\bar{a}, \tag{9}$$

$$a^N_{\min} = 0. \tag{10}$$

  Recall $p = 1 - \frac{1}{\bar{a}}\frac{c}{rI_t}$ if $I_t \geq \hat{I}_t$ and $p = 0$ if $I_t < \hat{I}_t$.

- If $p < q$, there is *excess supply* of seats of the STEM major. All who prefer the STEM major are admitted. There are still $q - p$ seats of the STEM major to be filled. These seats are taken by the bottom $q - p$ fraction of students in the skill distribution, who would not be admitted by their most preferred non-STEM major because of excess demand for the non-STEM major. Therefore,

$$AdSTEM = [0, (q-p)\bar{a}] \cup [(1-q)\,\bar{a}, \bar{a}], \tag{11}$$

$$AdNonSTEM = ((q-p)\bar{a}, (1-q)\bar{a}), \tag{12}$$

$$a^S_{\min} = 0, \tag{13}$$

$$a^N_{\min} = (q-p)\bar{a}. \tag{14}$$

Figure 2 depicts the relationship between $a_{\min}$ and I_t for both STEM and non-STEM majors. Clearly, when I_t experiences a large increase from a low level to a high level, $a^S_{\min}$ increases sharply while $a^N_{\min}$ plunges, thus enlarging the gap in admission cutoffs between STEM and non-STEM majors, $a^S_{\min} - a^N_{\min}$.[5] An increase in $a^S_{\min} - a^N_{\min}$ reflects a shift of high-skill students towards the STEM major.

Proposition 1. *When I_t increases, i.e., the current information projects more favorable prospects for STEM graduates, the gap in admission cutoffs, $a^S_{\min} - a^N_{\min}$, becomes bigger. An increase in $a^S_{\min} - a^N_{\min}$ reflects a shift of high-skill students toward the STEM major.*

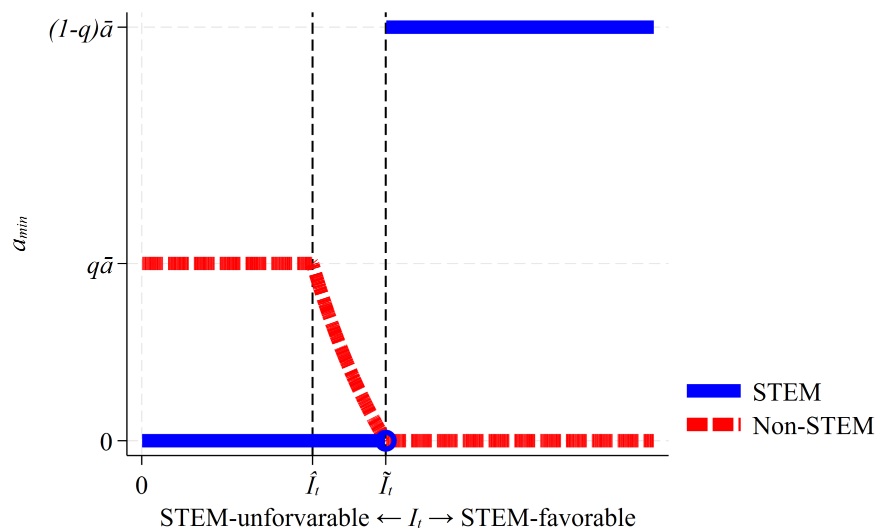

Figure 2: Minimum Ability of Admitted STEM Students

2.2 Hypotheses on the Trade War's Impacts

In light of the model presented above, how can the China-US trade war affect major choice? Our main argument is that the trade war's outbreak may alter current information on economic conditions (i.e., I_t in the model), thus changing beliefs about STEM graduates' prospects and influencing major choice. We also consider other possibilities. In the following, we outline our hypotheses, drawing upon existing evidence from economic literature as well as our observations of Chinese society.

The trade war may generate substantial economic uncertainty and raise people's concerns about economic development (Benguria et al., 2022; Alessandria et al., 2024). In particular, trade dynamics can influence labor market outcomes differentially across

[5] In Figure A1, we also examine the average ability of admitted students, $a^S_{avg} = E[a_i \mid AdSTEM]$ and $a^N_{avg} = E[a_i \mid AdNonSTEM]$. We observe similar patterns.

industries (Qiu et al., 2019; Fajgelbaum et al., 2020; Jiao et al., 2022). Upon observing these contemporaneous impacts, which enter I_t, students would alter their expectations of job prospects associated with different majors and react accordingly in major choices. The link between economic shocks and major choice has been well established by preexisting literature. For instance, Ersoy (2020) finds that the Great Recession led to a shift from recession-sensitive majors towards recession-resistant majors in the US. Blom et al. (2021) establish a more general relationship between business cycle and college major choice, showing that cohorts exposed to recessions during typical schooling years select majors that earn higher wages, have better employment prospects, and lead to work in a related field. Moreover, Weinstein (2022) demonstrates that the local labor market, as opposed to the national market, plays an important role in economic shocks' impacts on college major choice. Based on these insights and Proposition 1, if STEM graduates' labor market outcomes are relatively better under the trade war, we expect that there would be more skilled students sort into the STEM major, enlarging the gap in admission cutoffs between STEM and non-STEM majors (i.e., $a^S_{\min} - a^N_{\min}$ in the model). This effect may be more pronounced in more trade-war-vulnerable regions given the significance of local labor market conditions. Note that it is an empirical question of how the trade war differentially affects labor market outcomes across majors. We will shed light on this in our analysis. We summarize these predictions as a formal hypothesis.

Hypothesis 1 (Labor Market Hypothesis)**.** *The trade war can increase the gap in admission cutoffs between STEM and non-STEM majors ($a^S_{\min} - a^N_{\min}$), provided that it relatively improves STEM graduates' labor market outcomes. The effect should be stronger in more trade-war-vulnerable regions.*

Even in lieu of immediate changes in benefits, the trade war may forge an expectation of the nation's developmental strategy in the medium or longer run, triggering a shift of major choice toward certain fields in preparation for reaping prospective labor market opportunities. Specifically, the Trump Administration launched the trade war to contain China's "Made in China 2025" project (MIC 2025) that featured substantial state support for high-tech sectors (White House, 2018; Ju et al., 2024). The trade war accompanied the Administration's accusation of China's technology theft and sanctions on China's high-tech sectors. The semiconductor sector is one salient example: e.g., the Trump Administration blocked Chinese acquisition of US semiconductor firms (Reuters, 2018), restricted Chinese research institutions, and sanctioned flagship Chinese semiconductor firms like ZTE and Huawei. However, these external pressures could push China to strengthen its industrial policies to achieve a higher degree of technological self-reliance. Tellingly, under the trade war and associated technological sanctions, the Chinese government vowed to tackle tech bottleneck (*kabozi jishu* in Chinese) to secure development (Wall Street Journal, 2020). Hinted by these signals of national plans for technological development, that is, I_t increases, people may be motivated to pursue STEM majors, thereby increasing the gap in admission cutoffs between STEM and non-STEM majors (i.e., $a^S_{\min} - a^N_{\min}$ in the model). Note that this effect is contingent on knowledge of national plans.

Hypothesis 2 (Industrial Policy Hypothesis)**.** *The trade war can increase the gap in admission cutoffs between STEM and non-STEM majors ($a^S_{\min} - a^N_{\min}$), if it raises greater attention to China's industrial policies.*

The two hypotheses above relate to beliefs about pecuniary returns to different majors, which induces a sorting based on abilities. It is likely that the trade war intervenes major choice through *non-pecuniary* channels. An interesting and important one is nationalism. In particular, the Chinese state characterizes the trade war as an unprovoked attempt by the US to curb China's development, and it calls for solidarity of the Chinese people to confront challenges. These messages from the state can stimulate nationalism (Sha, 2021; Fan et al., 2022), making nationalistic students perceive a higher utility of enrolling in STEM majors and serving the country in the future. Were nationalism positively associated with ability, Proposition 1 suggests that we would also observe a larger gap in admission cutoffs between STEM and non-STEM majors (i.e., $a^S_{\min} - a^N_{\min}$ in the model).

Hypothesis 3 (Nationalism Hypothesis)**.** *The trade war can increase the gap in admission cutoffs between STEM and non-STEM majors ($a^S_{\min} - a^N_{\min}$), if high nationalism coincides with high ability.*

To investigate these hypotheses, we will first examine the evolution of the gap in admission cutoffs between STEM and non-STEM majors during the trade war. Then, building upon the findings, we will shed light on the role of labor market outcomes, industrial policy, and nationalism.

3 Data

3.1 College Admission Results

Our analysis is based on program-level admission results published by colleges after the end of each year's college entrance exam (*gaokao* in Chinese) and admission. Table 1 provides an example for an observation from these data. It shows that in 2016, Tsinghua University's computer science program admitted two science-track students from Shandong Province. Among these two admitted students, the minimum score is 702, which ranks the 47th in Shandong. This minimum requirement is linked with $a_{\min}$ in our model.

Table 1: An Example of College Admission Results

College	Year	Province	Track	Program	# Admitted	Min. Score	Ranking
Tsinghua University	2016	Shandong	Science	Computer Science	2	702	47

Note: This table displays an example of the data on college admission results.

We collect data on admission results during 2016–2019. We make the following restrictions when constructing the sample. First, we focus on colleges listed in the Project 985 and the Project 211, which are the best colleges in China.[6] There are in total 115 Project-985-or-211 colleges. We exclude three military colleges and one music college, since they have distinct admission procedures. This results in 111 colleges in our sample.[7] Second, there are two tracks in China's high school education and college admission, the arts track and the science track. We restrict our sample to science-track admission results, because the majority of STEM majors are only available to science-track students.[8] By contrast, science-track students can freely choose almost all kinds of majors. Third, we exclude admission results of Hainan, Xinjiang, Tibet, Shanghai, and Zhejiang. The former three are excluded because of data unavailability for certain years. The latter two are excluded because starting in 2017, they implemented a reform that removed the distinction between arts and science tracks in exam and admission, introducing complexities in analyzing the evolution of major choices. As a result, our sample covers 26 provinces. Finally, we exclude majors in art, which require admission professional skill exams and have different admission procedures; they account for only 0.3 percent of observations.In the end, our sample includes 237,399 observations.

3.2 Variables

Admission Cutoff. The main outcome in this paper is the admission cutoff. Specifically, for program j of major m at college c, its admission cutoff score in province p and t is defined

[6]We are aware that in 2015, the Chinese government initiated the Project of "World-Class University and Discipline Construction." However, this new project includes almost all colleges in the old Projects 985 and 211.

[7]The three military colleges are the National University of Defense Technology, the Naval Medical University, and the Air Force Medical University. The music college is the Central Conservatory of Music.

[8]To make sense of this, during 2016–2019, the STEM major programs available to arts-track students only account for 0.6 percent of all STEM major programs.

as:

$$P_{jmcpt} = \left(1 - \frac{\text{Lowest ranking}_{jmcpt}}{\text{Eligible students}_{pt}}\right) \times 100. \tag{15}$$

Take the admission result displayed in Table 1 as an example. In 2016, the lowest ranking of Shandong students admitted to Tsinghua University's computer science program was ranked 47th. In that year, a total of 175,843 science-track students in Shandong were eligible to apply to colleges (the rest of the ineligible ones could only apply to junior colleges). Therefore, the admission cutoff score in this case is $\left(1 - \frac{47}{175{,}843}\right) \times 100 = 99.97$, meaning that for a Shandong student to enter Tsinghua University's computer science program, they had to be ranked above at least the 99.97th percentile, or surpassed 99.97 percent of their peers in the same province. Apparently, the higher the admission cutoff, the more selective the program.

Major Classifications. Colleges may design their programs differently. We standardize major classifications for programs in our sample. To do so, we match programs' descriptive text with the major classifications by the Ministry of Education (MOE), which include 93 major categories and 792 subcategories.[9] In Appendix Table A1, we provide the list of STEM major categories that are defined by the MOE and so are used in this paper.

Covariates. There are several other factors that may influence admission. We consider two sets of factors and include them as controls in our regression analysis. The first set is about a college's admission policy. We will control for the number of students admitted. Because the admission quotas are almost always filled, the number of students admitted would reflect the quotas offered.[10] We will also control for a college's admission percentile score and the number of programs offered, which capture a college's overall selectivity and abundance of opportunities. The second set of covariates concerns the characteristics of a college's locating city. We focus on the city's economic development level, openness, and industrial structure, as measured by the (log) GDP per capita, the share of FDI in GDP, the share of foreign firms, and the shares of employment in different sectors. We obtain these data from the City Statistical Yearbooks.

Summary Statistics. Table 2 presents the summary statistics of the main variables. In our sample, a large fraction of observations are STEM majors. Unsurprisingly due to our concentration on Projects 985 and 211 colleges, majors in our sample exhibit high selectivity.

[9] The full list of major classifications can be found at the Ministry of Education's website (http://www.moe.gov.cn/srcsite/A08/moe_1034/s4930/202304/W020230419336779992203.pdf). The matching is done based at the subcategory level. We first use a fuzzy text matching approach. Then for those that cannot be matched with great precision, we conduct manual matching.

[10] In our data, we do not observe quotas, so we use the number of students admitted as a compromise.

The average major requires a ranking of at least the 90th percentile.

Figure 3 compares the average admission percentile scores between STEM and non-STEM majors, net of the college-by-province average. Clearly, it shows that the (relative) average admission percentile evolved similarly prior to 2017. But after 2018, the year when the China-US trade war unfolded, a divergence emerged and the gap in admission percentile scores increased. This figure motivates our subsequent investigations.

4 Evolution of the Gap in Admission Cutoffs

4.1 Empirical Strategy

Estimating Equation. Inspired by Figure 3, we employ the following difference-in-differences (DiD) specification to estimate the change in the gap in admission cutoffs between STEM and non-STEM majors:

$$P_{jmcpt} = \beta\,(STEM_m \times Post_t) + \lambda_{pm} + \mu_{pc} + \delta_{pt} + X'_{jmcpt}\gamma + \varepsilon_{jmcpt}. \tag{16}$$

In Equation 16, the dependent variable, P_{jmspt}, is the admission cutoff of program j under major m at college c among students admitted in province p and year t, as defined by Equation 15. We include a set of fixed effects to account for heterogeneity in P_{imcpt}. λ_{pm}, μ_{pc}, and δ_{pt} are the province-by-major, province-by-college, province-by-year fixed effects, respectively.[11] Note that we allow the fixed effects at major, college, and time levels to vary flexibly across provinces, because each province undertakes its own *gaokao* and admission. X_{jmcpt} includes a set of covariates mentioned in Section 3.2. $STEM_m$ is a dummy variable that equals one if m is an STEM major. $Post_t$ is a dummy variable for years after 2018, the year when the trade war unfolded. ε_{jmcpt} is the error, which is clustered at the province-by-major level.

Identification and Interpretation. β is the parameter of interest in Equation 16. Let $\hat{\beta}$ denote the OLS estimator of β; it is estimated through comparing the paths of admission cutoffs between STEM and non-STEM majors, as in conventional DiD designs. Under the parallel trends assumption that the admission cutoffs would have evolved identically between majors in the absence of the trade war, $\hat{\beta}$ captures the *change in the gap* in admission cutoffs between STEM and non-STEM majors. If $\hat{\beta} > 0$, the cutoff gap is widened and STEM majors become more selective than non-STEM majors after 2018, and the opposite is true if

[11]For the major fixed effects, we use major categories (N = 93).

$\hat{\beta} < 0$.

Two remarks are in order. First, the interpretation of $\hat{\beta}$ speaks to a change in the cutoff *gap*, rather than a change in the cutoff *level* of STEM majors as in conventional DiD designs. This is because in our setting, due to admission market clearing, an increase in STEM cutoffs is necessarily associated with a decrease in non-STEM cutoffs, as also shown by the simple model in Section 2. That said, a shock in our setting has spillovers and affects treatment (STEM) and comparison (non-STEM) groups simultaneously, unlike conventional DiD designs where only the treatment group is affected while the comparison group is intact. However, identifying the effect on the cutoff gap only requires the parallel trends assumption. Due to spillovers, it is challenging to identify the effect on the cutoff level of STEM majors, unless strong assumptions are imposed to discipline spillovers (Butts, 2021). Nonetheless, as we elaborate in Section 2, the change in cutoff gap is informative for underlying behavioral changes in major choice.

Second, admittedly, $Post_t$ is a crude measure of exposure to the trade war, which only leverages temporal variation. Though the China-US trade war was a salient shock in 2018, it is possible that there were other contemporaneous shocks in effect from 2018 onward that also affected major choice, which can confound the interpretation of $\hat{\beta}$. We take the analysis by Equation 16 as a simple starting point to understand the overall patterns. In Section 5, we will shed further light on the role of the trade war by leveraging granular, local variation in exposure to the trade war.

4.2 Results

Table 3 presents the estimates of Equation 16. Column (1) is a minimum specification that only includes fixed effects. Columns (2) and (3) stepwise include variables on college admission policy and college location. The estimates show that after 2018, the gap in admission cutoffs between STEM and non-STEM majors is widened, suggesting that more high ability students flow to STEM majors.

An idiosyncratic flow of high ability students towards STEM majors can also mechanically enlarge the cutoff gap. To ascertain that the results above are simply by chance, we perform a placebo exercise following Bleemer and Mehta (2022). We permute the STEM major status and fit Equation 16 over the counterfactual dataset to get a counterfactual $\hat{\beta}$ (full specification, Column (3) in Table 3). We repeat this procedure 1,000 times and use the resulting distribution to estimate the empirical two-sided p-value of the actual $\hat{\beta}$. Figure 4 compares the true estimate with the empirical distribution of counterfactual estimates.

The true estimate's magnitude appears to be highly distinctive, implying that the effect is unlikely due to an idiosyncratic shock that mechanically enlarges the cutoff gap. Rather, there ought to be some material behavioral changes in major choice.

Figure 5a displays the estimates of an event-study specification modified from Equation 16, which enables us to examine the changes year by year. Apparently, there are no significant pretrends. But after 2018, we see a sharp jump in the cutoff gap. Such patterns favor the identifying assumption that admission cutoffs would have evolved similarly between majors were there no shocks. We also implement a sensitivity test proposed by Rambachan and Roth (2023) to evaluate the distinctiveness of the jump in 2018. The idea for this test is to allow the violation of parallel trends in the post-2018 period to be $\bar{M}$ times of the pretrends, and then one can test whether the post-2018 effect is still statistically significant conditional on the hypothetical violation of parallel trends. Figure 5b reports this test. Apparently, the the post-2018 effect withstands a large degree of parallel-trend violations; it is statistically significant at the 5 percent level even if we allow the violation to be near three times of the pretrends.

5 Illuminating the Role of China-US Trade War

Thus far, our results have documented that the gap in admission cutoffs between STEM and non-STEM majors increased after 2018. To what extent did the trade war drive these changes? In this section, we conduct further investigations to shed light on the role of trade war.

5.1 Measuring Local Exposure to the Trade War

Underpinning our investigation is the uneven exposure to the trade war across regions. Existing studies have shown that the trade war impacted China not only economically (Chor and Li, 2021) but also ideologically (Fan et al., 2022; Sha, 2021), and these impacts were more pronounced in highly exposed regions. In the same vein, the trade war may affect major choice to a greater extent in highly exposed regions through the channels outlined in Section 2, including labor market, attention to industrial policy, and nationalistic sentiments.

We construct a Bartik-style variable to measure provincial-level exposure to the trade war in terms of the Trump tariffs:[12]

$$Tariff_{pt} = \sum_{n} \left(\frac{L_{pn}}{L_p} \frac{E^{US}_{pn}}{E^{ROW}_{pn}} \right) \Delta\tau_{nt}. \tag{17}$$

It is a weighted sum of Trump tariffs. τ_{nt} is the additional tariff imposed by the Trump Administration on six-digit HS industry n as of year t, which we obtain from Li et al. (2020). $\frac{L_{pn}}{L_p}$ is the employment share of industry n in province p, measured using the 2008 Chinese economic census. $\frac{E_{pn}}{E_p}$ is province p's share of exports to the US in its industry n, calculated using the 2016 Chinese customs data. Therefore, it is straightforward that $Tariff_{pt}$ is higher if a province has a high concentration of employment in the high-Trump-tariff industries and it has a strong reliance on the US market in those industries.

5.2 Regional Heterogeneity in Cutoff Gap Changes

To start with, we estimate Equation 16 separately by province, yielding province-specific cutoff gap changes. Figure 6a displays that the cutoff gap changes by province. Most provinces witnessed an increase in the cutoff gap, but there is large heterogeneity. Figure 6b plots the provincial-level cutoff change against exposure to Trump tariffs as of 2019, $Tariff_{p,2019}$. There is a tight linear relationship: highly exposed provinces experienced a larger increase in the cutoff gap. Specifically, a 1 SD increase in exposure to Trump tariffs relates to a 0.5 SD larger increase in the cutoff gap. R^2 indicates that exposure to Trump tariffs can explain 25% of the variance in the cutoff gap change across provinces.

Then, we estimate the following model:

$$\begin{aligned} P_{jmspt} = {} & \pi \left(STEM_m \times Post_t \times Tariff_{p,2019} \right) + \beta \left(STEM_m \times Post_t \right) \\ & + X'_{jmspt}\gamma + \lambda_{pm} + \mu_{ps} + \delta_{pt} + \varepsilon_{jmspt}. \end{aligned} \tag{18}$$

This is essentially a triple-differences model, which examines how the cutoff gap change depends on a province's exposure to Trump tariffs, as Figure 6b does. Coefficient π captures the heterogeneity in the cutoff gap change by $Tariff_{p,2019}$. $Tariff_{p,2019}$ is standardized to have mean 0 and SD 1. The identification assumption for π is: conditional on the controls, $Tariff_{p,2019}$ is not associated with other unobserved provincial-level factors that can cause differential evolution in the cutoff gap.

[12]College admission is conducted at the provincial level, making the provincial level a sensible level to compare admission results. If information on students' origins is available, it is possible to use more disaggregated exposure (e.g., at the city level). However, such data are not available to us.

Table 4 presents the estimates of Equation 18. Column (1) adopts the baseline specification given by Equation 18. It shows that the cutoff gap increases more after 2018 if $Tariff_{p,2019}$ is higher, consistent with the observation from Figure 6b. The rest columns explore the robustness of this finding. Column (2) is a more demanding specification, which replaces $STEM_m \times Post_t$ with major-by-year fixed effects. However, the estimate does not change markedly. Column (3) attempts to address the concern that $Tariff_{p,2019}$ might pick up the effects of other provincial-level factors. To do so, we include the interactions of $STEM_m$, year indicators, and predetermined provincial factors (measured in 2015). We consider three factors that may correlate with exposure to Trump tariffs: (i) log GDP per capita, (ii) trade openness (measured by the share of exports and imports in GDP), and (iii) the share of manufacturing employment. Nonetheless, introducing such interaction terms in fact accentuates the heterogeneity by exposure to Trump tariffs.

In addition, we estimate the following dynamic specification:

$$\begin{aligned} P_{jmspt} = & \sum_{\tau \neq 2017} \pi_\tau \left[STEM_m \times I_{\{t=\tau\}} \times Tariff_{p,2019} \right] + \beta \left(STEM_m \times Post_t \right) \\ & + X'_{jmspt}\gamma + \lambda_{pm} + \mu_{ps} + \delta_{pt} + \varepsilon_{jmspt}. \end{aligned} \tag{19}$$

$I_{\{t=\tau\}}$ is an indicator for year τ. Thus, π_τ's capture the heterogeneous effects due to Trump tariffs in each year. Figure 7 presents estimated π_τ's. Clearly, the Trump-tariff-induced heterogeneous effect only occurred after 2018, when the trade war actually broke out. This pattern strengthens the validity of our triple-differences design.

5.3 Evidence on Potential Channels

Thus far, our results underscore that exposure to the trade war causes a shift of high-ability students to STEM majors. Through which channels does the trade war intervene in major choices? In the following, we shed light on the hypotheses outlined in Section 2.

Labor Market Hypothesis. Hypothesis 1 proposes that the trade war may have heterogeneous impacts on returns to different majors, thus, students would be prompted to choose STEM majors if STEM graduates perform relatively better in the labor market under the trade war. To investigate this issue, we utilize the 2014 and 2018 surveys of the China Family Panel Study (CFPS), which offer information on individual income as well as majors.[13] We focus on a balanced panel of individuals who were aged 25–60 in 2014,

[13]There is a 2016 CFPS survey. We do not use this wave because income data are missing for many individuals due to survey implementation failure; this wave also does not provide information on majors.

and estimate a first-difference model:

$$\Delta Income_i = \beta Tariff_{p,2018} + X_i'\gamma + \varepsilon_i. \tag{20}$$

$\Delta Income_i$ is the growth rate in individual i's income between 2014 and 2018. Note that the first differencing effectively controls for individual fixed effects. $Tariff_{p,2018}$ is province p's exposure to Trump tariffs as of 2018. X_i includes rich individual characteristics, including indicators for gender, birth cohorts, college attendance, college major, urban residency, and communist party membership.

Table 5 presents the results. The trade war reduces income, but the negative effect is much smaller for college graduates, especially STEM graduates, offering support for Hypothesis 1 that students may sort into STEM majors under the trade war due to more resilient labor market performance of STEM graduates.

Industrial Policy Hypothesis. Hypothesis 2 argues that the trade war may raise attention to China's industrial policy and thus motivate students towards STEM majors in preparation for reaping future opportunities. To shed light on this argument, we examine people's attention to Chinese industrial policy using Baidu search data.[14] We focus on two relevant keywords: (i) "Made in China 2025" (*zhongguozhizao 2025* in Chinese) and (ii) "chip" (*xinpian* in Chinese). Regarding (i), the MIC 2025 plan was proposed in 2015. It was an initiative which strives to secure China's position a global powerhouse in high-tech industries; it also outlined industries that the state should support strongly, such as information technology, robotics, aerospace hardware, etc.[15] As mentioned in Section 2, the trade war was launched to contain the MIC 2025 plan, and Trump tariffs primarily targeted at manufactured goods included by the plan (White House, 2018; Ju et al., 2024). Regarding (ii), chips, or semiconductors in general, are a product that China is subject to heavy constraints by the US and its allies. Under the China-US trade war and deteriorating China-US relations, China's access to chips face significant restrictions. For example, in recent years, the US and its allies imposed a chip export ban against China. Thus, chips gain particular salience in the public discourse concerning China's quest for tech self-sufficiency.[16]

In Figure 8, we start by examining the raw national trends in attention to several topics.

[14] Baidu is the Chinese counterpart of Google, which takes a 70 percent market share of the search engine market. Previous research have demonstrated that search data can be informative about people's behaviors (Alm et al., 2022; Qin and Zhu, 2018).

[15] See https://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm

[16] http://www.xinhuanet.com/world/2018-01/22/c_129795850.htm

In Figure 8a, unsurprisingly, there is a spike in searches for the trade war after its outbreak. We use searches for "China-US trade war", "China-US trade friction", and "trade war" as well as the aggregation of the three, following Fan et al. (2022).

With respect to attention to China's industrial policy, there is a spike in searches for "Made in China 2015" after the Trump Administration declared the trade war in March 2018. In fact, this spike is only slightly smaller than the spike in March 2015 when the MIC 2025 plan was first proposed in the 12th National People's Congress. Similarly, searches for "chip" also exhibited a spike following the outbreak of the trade war.

Using a 2016–2019 panel dataset of 26 provinces included in our admission data, we estimate the following DiD model to test the trade war's impact on attention to China's industrial policy:

$$Y_{pt} = \beta_1 \left(Tariff_{p,2019} \times Post_t \right) + \beta_2 Tariff_{p,2019} + \beta_3 Post_t + X'_{pt}\gamma + \varepsilon_{pt}, \tag{21}$$

where Y_{pt} is the Baidu search volume for a certain topic in province p and year t. Table 6 shows that provinces more exposed to the trade paid more attention to to China's industrial policy deployment. Figure 9 presents the event-study plots, confirming the sharp changes in the wake of trade war. These results corroborate Hypothesis 2 that the trade war may alter major choice through raising attention to China's industrial policy.

Nationalism Hypothesis. We now turn to examine Hypothesis 3, which suggests that the widened cutoff gap can be due to nationalistic, high-ability students' shift towards STEM majors. Indeed, amidst the trade war, state propaganda called for self-strengthening of key technologies to overcome reliance on the US, and nationalistic, anti-American sentiments escalated in China (Fan et al., 2022; Sha, 2021). Relatedly, existing evidence suggests that consumer behaviors can be influenced by nationalism or political attitudes in general (Fisman et al., 2014; Heilmann, 2016; Fouka and Voth, 2023; Wang et al., 2022).

Are nationalistic sentiments at play in major choice? If so, one would expect the cutoff gap change to be larger in traditionally more nationalistic regions. People in these regions are more likely to buy into nationalistic narratives and react accordingly. In addition, there would be a greater overlap between high ability students and nationalistic students, who are the compilers of the nationalism channel. Therefore, we explore if the cutoff gap change is heterogeneous by the level of nationalism.

We employ three variables to capture the level of preexisting nationalism or the tendency that people may buy into the nationalistic narratives: (i) whether a province was passed by the Red Army's Long March that featured intense pro-communist propaganda and recruitment of party members, (ii) the provincial-level government penetration on the Internet (Qin and Zhu, 2018), (iii) a provincial-level nationalism measure constructed using the World Value Survey (WVS) following Lan and Li (2015).

Table 7 displays the results of our investigation. There is no discernible heterogeneity by nationalism, suggesting that nationalism cannot explain our findings. Furthermore, in Figure 10, based on the WVS, we find no strong correlation between nationalism and ability (measured by educational attainment), which, again, indicates that the widened cutoff gap is not because the trade war shifts nationalistic students, who tend to have high abilities, towards STEM majors.

Taken together, our results indicate that the main motive behind high-ability students' shift toward STEM majors is career considerations based on observed advantages of STEM graduates or beliefs about national development rather than nationalistic sentiments.

6 Conclusions

In this paper, we contribute a novel perspective of understanding the consequences of the China-US trade war: the impact on human capital development, with a particular focus on how it shapes the choice of college majors. Relying on a simple model, we propose several hypotheses of the mechanisms through which the trade war may influence students' major choices. The model suggests that information signaling higher returns for STEM graduates can motivate students to opt for these disciplines. In particular, we identify scenarios where the trade war may induce a shift of ability students toward STEM majors: when the trade war improves job prospects of STEM graduates, directs attention to China's industrial policies, or coincides with elevated nationalist sentiments among high-ability individuals.

We leverage a unique dataset of college admission data to examine the model's implications. Employing a difference-in-differences (DID) methodology, we document that the trade war stimulated a shift of high-ability students toward STEM fields. This shift is more pronounced in provinces strongly affected by additional US tariffs, which underscores the localized nature of the impact of economic tensions on human capital development. Our further empirical analysis indicates that the change in major choice behavior is due to (i) the resilient labor market performance of STEM graduates and (ii) the faith in the country's pursuit of self-reliant technological development that favors STEM graduates. In contrast, there is no evidence that growing nationalism under the trade war affected major choices.

By bringing to light the impact of the China-US trade conflict on college major choice among Chinese students, our paper underscores the importance of understanding how human capital development can be shaped by (de)globalization. We close this paper by noting some avenues for future research. Firstly, our paper is nonetheless focused on short-term effects. It would be interesting to evaluate the trade conflict's long-term effects on human capital development, which can yield richer insights. Secondly, while major choice is a building block for human capital development, other subsequent, related decisions can be equally important, such as migration and allocation of talents across industries and regions. These issues are worthy of further, rigorous investigation. Lastly, more granular data, such as information on student characteristics (e.g., family backgrounds), can allow for a more in-depth analysis of the heterogeneous effects: for instance, who is least able to catch information and adjust major choice? This can not only improve our understanding of the nature of human capital development but also inform appropriate policy support for students and households.

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Figures

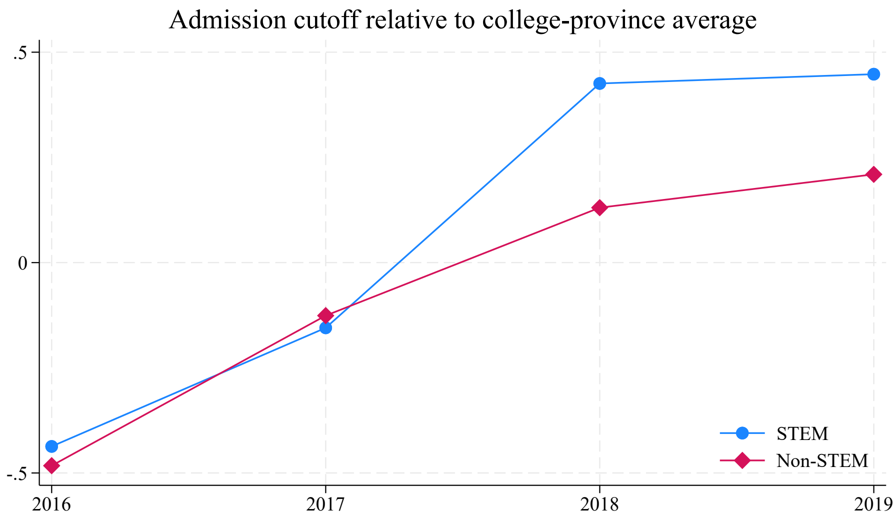


Figure 3: Average Admission Cutoff Relative to College-by-Province Average

Note: This figure presents the time series of (conditional) average admission cutoff for STEM and non-STEM majors. The college-province specific average cutoff is partialled out from the admission cutoff before aggregating to the major level.

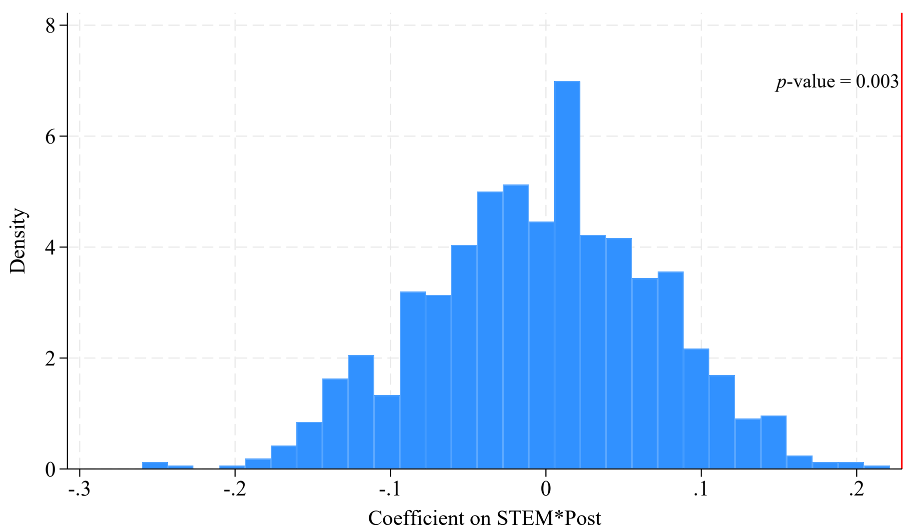
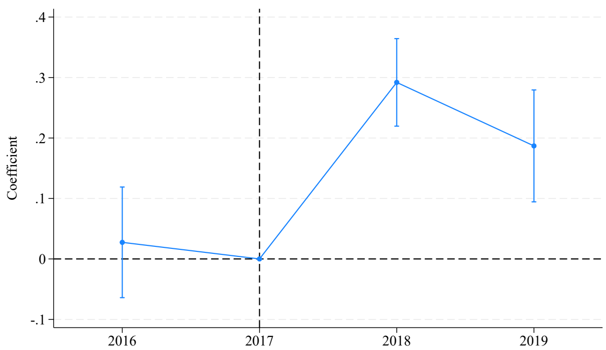
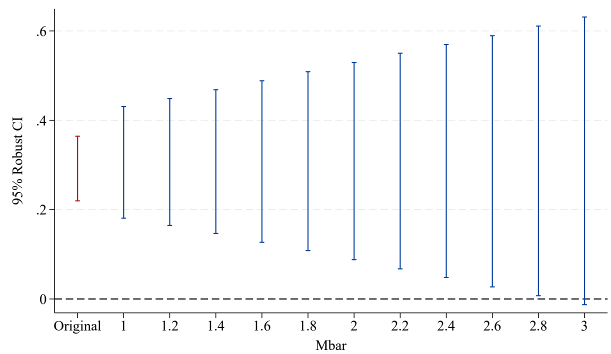


Figure 4: Permutation Test

Note: This figure presents the results of a permutation test. We permute the STEM major status and fit Equation 16 over the counterfactual dataset to get a counterfactual $\hat{\beta}$. We repeat this procedure 1,000 times, and use the resulting distribution (the bars in the figure) to estimate the empirical two-sided p-value of the actual $\hat{\beta}$ (the vertical line in the figure).



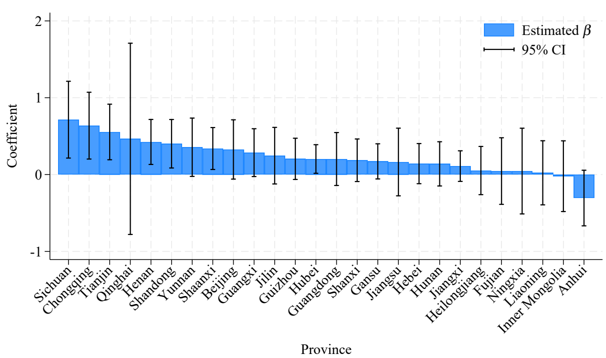
(a) Event-Study Estimates



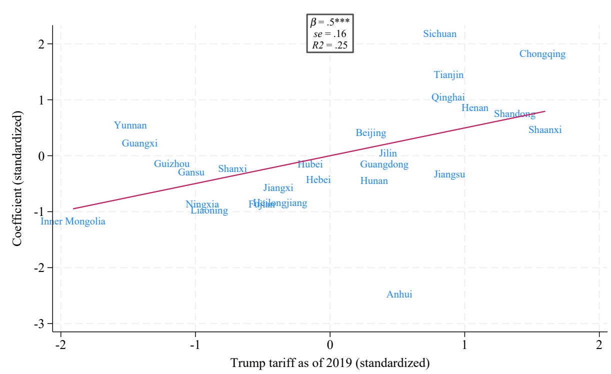
(b) Sensitivity Test

Figure 5: Event-Study Estimates and Sensitivity Test

Note: Figure 5a displays the dynamics in the cutoff gap using an event-study model. 95% confidence intervals are displayed. In Figure 5b, we implement the test proposed by Rambachan and Roth (2023) to assess the 2018 jump's sensitivity when allowing the violations of parallel trends to be $\bar{M}$ times of the pretrends.



(a) Cutoff Gap Changes by Province



(b) Relationship with Trump Tariffs

Figure 6: Cutoff Gap Changes and Trump Tariffs

Note: Figure 6a displays that cutoff gap changes by province, estimated by running Equation 16 separately for each province. Figure 6b plots the provincial-level cutoff change against exposure to Trump tariffs as of 2019, $Tariff_{p,2019}$, as defined in Equation 17.

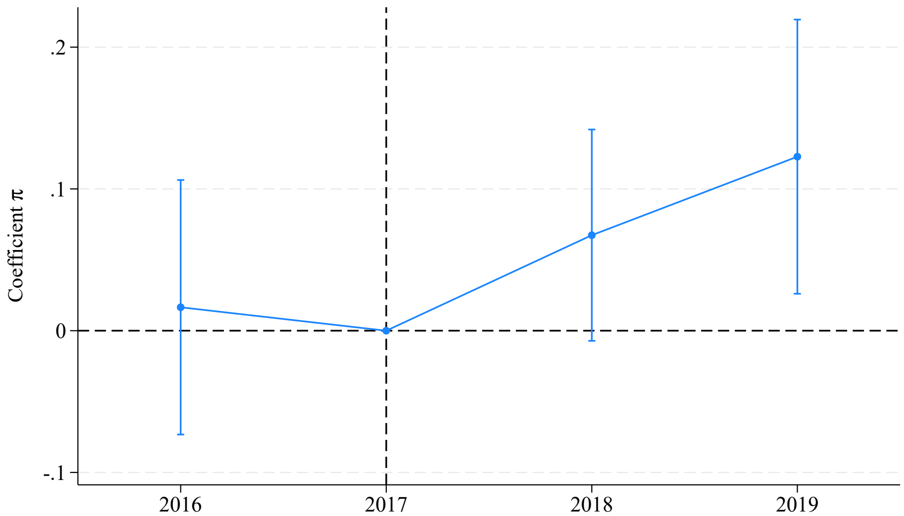
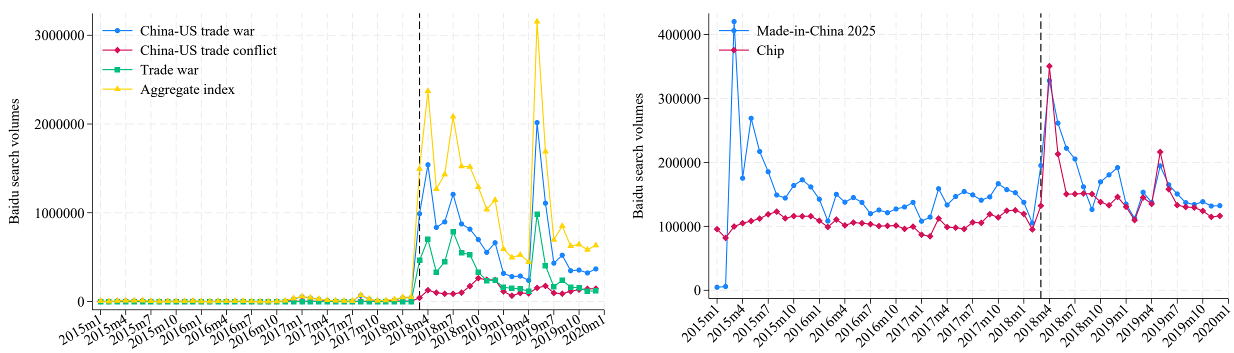


Figure 7: Dynamics of Heterogeneous Effects by Exposure to Trump Tariffs

Note: This figure reports the estimates of π_τ's in Equation 19, which capture the dynamics of heterogeneous changes in the cutoff gap by exposure to Trump tariffs. 95% confidence intervals are displayed.



(a) Trade-War-Related Keywords

(b) Industrial-Policy-Related Keywords

Figure 8: Time Series of Baidu Searches

Note: This figure presents the time series of Baidu searches for different keywords. Figure 8a concerns trade-war-related keywords. We use searches for "China-US trade war", "China-US trade friction", and "trade war" as well as the aggregation of the three. Figure 8b concerns two keywords related to China's industrial policy: "Made in China 2025" and "Chip." The dashed vertical line marks March 2018, the time when the Trump Administration declared the trade war.

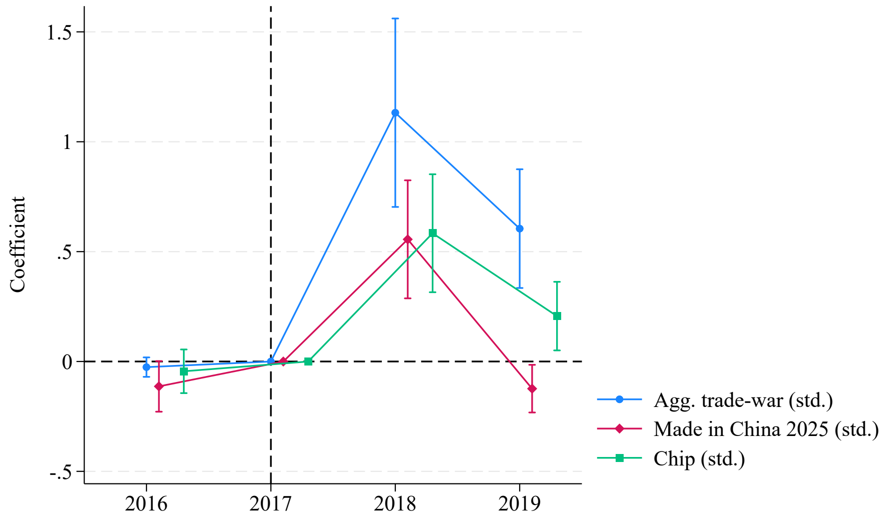


Figure 9: Dynamic Effects of Trump tariffs on Baidu Searches

Note: This figure displays the dynamic effects of exposure to Trump tariffs on searches for different topics on Baidu, including trade war (with three keywords aggregated), "Made in China 2025", and "Chip." 95% confidence intervals are displayed.

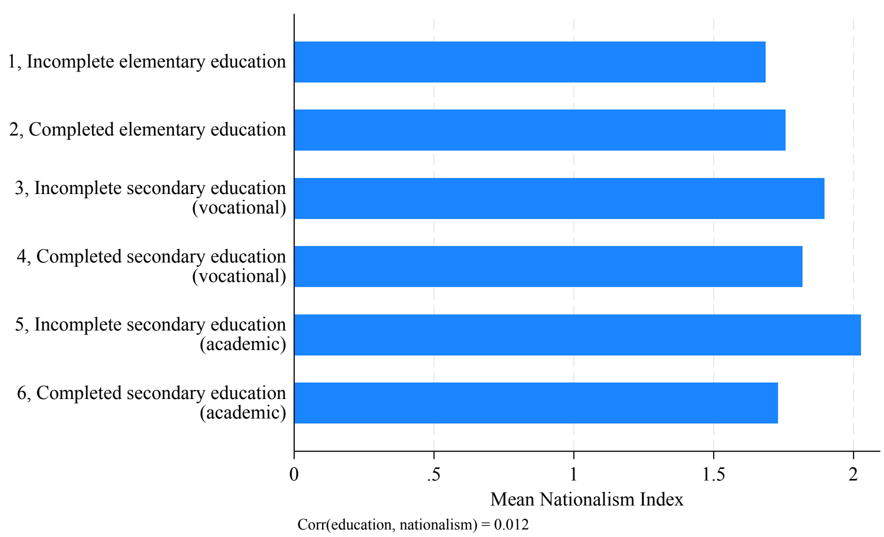


Figure 10: Nationalism by Educational Attainment

Note: This figure displays the average nationalism index by education group, based on the World Value Survey for China between 2001 and 2013. In the bottom of the figure, we present a correlation coefficient between the nationalism index and the level of educational attainment (estimated using individual-level data).

Tables

Table 2: Summary Statistics

	N (1)	Mean (2)	SD (3)	P10 (4)	Median (5)	P90 (6)
Admission percentile score	237,399	90.002	9.360	79.564	92.238	98.474
STEM	237,399	0.651	0.477	0	1	1
College admission percentile score	237,399	85.663	13.171	69.349	89.148	97.715
# Majors offered	237,399	27.811	15.320	10	26	48
# Students admitted	237,399	4.966	10.975	1	3	8
Log GDP p.c.	237,399	11.556	0.329	11.058	11.653	11.937
% FDI/GDP	237,399	0.485	0.260	0.100	0.498	0.759
% Foreign firms	237,399	16.710	10.510	4.886	14.680	31.365
% Financial sector employment	237,399	4.779	1.884	2.213	4.779	7.258
% Sci & tech employment	237,399	4.398	2.288	1.980	3.884	8.714
% Manufacturing employment	237,399	20.603	9.717	9.083	20.295	29.822

Note: This table displays the summary statistics of main variables in this paper. Data sources: college admission results and China City Statistical Yearbooks.

Table 3: Evolution of the Gap in Admission Cutoffs Between STEM and Non-STEM Majors

	Dependent: admission cutoff		
	(1)	(2)	(3)
STEM × Post	0.272***	0.235***	0.229***
	(0.043)	(0.039)	(0.039)
College admission cutoff		0.185***	0.184***
		(0.007)	(0.007)
# Majors offered		0.015***	0.016***
		(0.002)	(0.002)
# Students admitted		-0.018***	-0.018***
		(0.003)	(0.003)
Log GDP p.c.			-0.224
			(0.166)
% FDI/GDP			0.440***
			(0.047)
% Foreign firms			0.021***
			(0.006)
% Financial sector employment			0.131***
			(0.015)
% Sci & tech employment			0.309***
			(0.036)
% Manufacturing employment			0.047***
			(0.008)
Specification	FEs	+ College admission	+ College location
N	237,399	237,399	237,399
R-sq	0.868	0.878	0.878

Note: This table reports the estimates of Equation 16. From Column (1) to Column (3), controls are included stepwise in the regression. Fixed effects (FEs) include province-by-school, province-by-major, and province-by-year fixed effects. Variables on college admission and college location are shown in the table. Standard errors are clustered at province-by-school level, and they are reported in the parentheses.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 4: Triple-Differences Estimates

	Dependent: admission cutoff		
	(1)	(2)	(3)
STEM × Post × Trump tariff as of 2019 (std.)	0.086**	0.082**	0.128***
	(0.040)	(0.032)	(0.040)
STEM × Post	0.228***		
	(0.039)		
Major-by-year FE		Yes	Yes
STEM × year FE × provincial factors 2015			Yes
N	237,399	237,399	237,399
R-sq	0.878	0.879	0.879

Note: This table reports the estimates of Equation 18. All regressions include a full set of fixed effects (province-by-school, province-by-major, and province-by-year fixed effects) and covariance on college admission and college location. Column (2) further includes major-by-year fixed effects. Column (3) adds interactions between the STEM indicator, year indicators, and provincial factors measured in 2015. The factors are: (i) log GDP per capita, (ii) trade openness (measured by the share of exports and imports in GDP), and (iii) the share of manufacturing employment. Standard errors are clustered at province-by-school level, and they are reported in the parentheses.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 5: Trade War and Individual Income

	Dependent: ΔIndividual income		
	(1)	(2)	(3)
Trump tariff as of 2018 (std.)	-0.058**	-0.077**	-0.078**
	(0.024)	(0.029)	(0.029)
Trump tariff as of 2018 (std.) × College		0.091***	0.061**
		(0.030)	(0.025)
Trump tariff as of 2018 (std.) × STEM			0.107***
			(0.032)
Individual covariates	Yes	Yes	Yes
N	5,424	5,424	5,424
R-sq	0.034	0.036	0.036

Note: This table reports the impact of the trade war on income based on Equation 20. The dependent variable is the change in a person's income growth from 2014 to 2018. Individual covariates include indicators for gender, birth cohorts, college attendance, college major, urban residency, and communist party membership. Standard errors clustered at the provincial level are reported in the parentheses.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 6: Trade War and Baidu Searches

	Agg. trade-war (std.)			Made in China 2025 (std.)			Chip (std.)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trump tariff as of 2019 (std.) × Post	0.832***	0.832***	0.883***	0.207***	0.207***	0.275***	0.330***	0.330***	0.419***
	(0.160)	(0.160)	(0.169)	(0.067)	(0.068)	(0.080)	(0.086)	(0.086)	(0.109)
Trump tariff as of 2019 (std.)	0.017***		-0.356***	0.632***		0.107	0.516***		-0.056
	(0.003)		(0.112)	(0.097)		(0.155)	(0.097)		(0.161)
Post	0.978***		1.004***	0.263***		0.154	0.499***		0.446***
	(0.173)		(0.199)	(0.071)		(0.174)	(0.106)		(0.161)
% Mfg. employment			3.887***			4.185**			6.005***
			(1.032)			(1.929)			(1.645)
% Internet coverage			0.534			1.657			2.730**
			(0.721)			(1.159)			(1.278)
Log GDP p.c.			0.133			0.462			-0.010
			(0.240)			(0.411)			(0.372)
Province FE		Yes			Yes			Yes	
Year FE		Yes			Yes			Yes	
Time-varying controls			Yes			Yes			Yes
N	124	124	124	124	124	124	124	124	124
R-sq	0.669	0.849	0.767	0.289	0.913	0.623	0.323	0.923	0.730

Note: This figure displays the impacts of the trade war on Baidu searches for different topics: trade war, Made in China, and Chip. We present three specification for each dependent variable: (i) basic difference-in-differences, (ii) including province and year fixed effects, and (iii) including time-varying provincial controls. Standard errors clustered at the provincial level are reported in the parentheses.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 7: Nationalism and Major Choice

	(1) Long March	(2) Govt. online penetration	(3) WVS nationalism	(4) Long March	(5) Govt. online penetration	(6) WVS nationalism
STEM × Post	0.186***	0.267***	0.265***			
	(0.051)	(0.055)	(0.061)			
STEM × Post × High nationalism	0.096	-0.084	-0.100			
	(0.079)	(0.078)	(0.079)			
STEM × Post × Trump tariff as of 2019 (std.)				0.104**	0.139***	0.084*
				(0.048)	(0.050)	(0.048)
STEM × Post × Trump tariff as of 2019 (std.) × High nationalism				-0.041	-0.101	-0.025
				(0.066)	(0.066)	(0.077)
N	237,399	237,399	229,922	237,399	237,399	229,922
R-sq	0.878	0.878	0.875	0.879	0.879	0.876

Note: This table reports the heterogeneity in cutoff gap changes by nationalism. Columns (1)–(3) report the results for the DiD specification, while Columns (4)–(6) are built upon the triple-differences specification. All regressions include a full set of fixed effects (province-by-school, province-by-major, and province-by-year fixed effects) and covariance on college admission and college location. We adopt three measures of nationalism: (i) whether a province was passed by the Red Army's Long March that featured intense pro-communist propaganda and recruitment of party members, (ii) the provincial-level government penetration on the Internet (Qin and Zhu, 2018), (iii) a provincial-level nationalism measure constructed using the World Value Survey (WVS) following Lan and Li (2015). Standard errors are clustered at province-by-school level, and they are reported in the parentheses.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Appendix (For Online Publication Only)

I Additional Figures

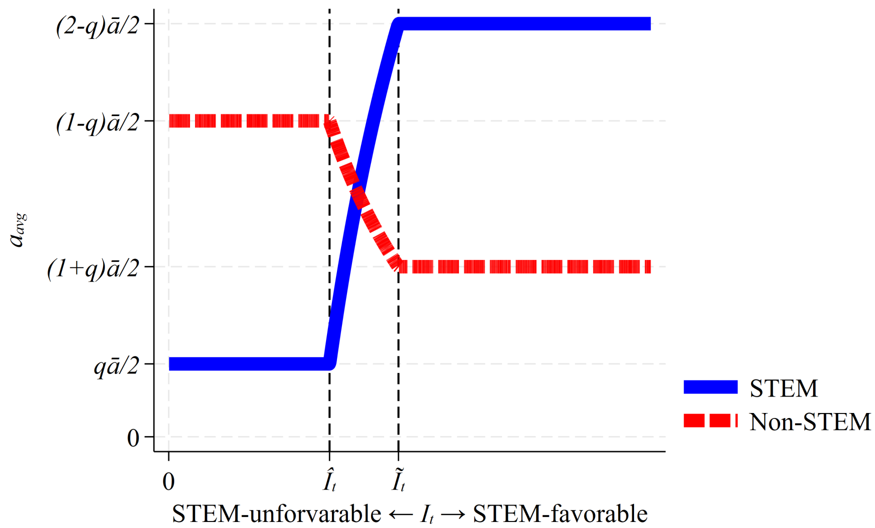


Figure A1: Average Ability of Admitted STEM Students

II Additional Tables

Table A1: STEM Majors

No.	Major	No.	Major
1	Textile	22	Bioengineering
2	Biomedical Engineering	23	Civil Engineering
3	Food Science and Engineering	24	Geophysics
4	Transportation	25	Atmospheric Science
5	Public Security Technology	26	Surveying and Mapping
6	Construction	27	Physics
7	Electronic Information	28	Astronomy
8	Geography	29	Safety Science and Engineering
9	Mechanical	30	Forestry Engineering
10	Computer Class	31	Automation
11	Mathematics	32	Mechanics
12	Weapons	33	Nuclear Engineering
13	Energy Power	34	Psychology
14	Electrical Engineering	35	Statistics
15	Material	36	Biological Sciences
16	Marine Science	37	Aerospace
17	Agricultural Engineering	38	Water Conservancy
18	Chemistry	39	Ocean Engineering
19	Chemical and Pharmaceutical Engineering	40	Instrument
20	Geology	41	Mining
21	Light Industry	42	Cross Engineering

Note: This table tabulates the STEM major categories.