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Defensive Innovation: Technological Rivalry and College Major Choice

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Defensive Innovation: Technological Rivalry and College Major Choice*

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Abstract

This paper studies the responses of students' college major choices to trade tensions in the context of the U.S.-China trade war. By analyzing granular college admissions data, we find that the U.S. tariffs targeting China's high-tech industries unexpectedly raised admission scores for STEM majors. A 1 percentage point increase in the weighted average tariff correlates with a 2% to 3% rise in standardized admission scores, particularly for engineering disciplines and elite universities. This phenomenon results from the "defensive innovation", where increased government support and private innovation investments in affected industries lead to greater demand for high-skilled workers. As U.S. tariffs rose, Chinese firms received more subsidies, enabling them to offer higher wages and more R&D related job opportunities, which incentivized students to pursue majors critical to the development of key strategic industries.

Keywords: Trade War, College Major Choice, Defensive Innovation, Industrial Policy

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1 Introduction

College major matters. This choice plays a pivotal role in shaping a student's career trajectory, earnings potential, job satisfaction, and personal fulfillment (Arcidiacono, 2005; Altonji, Blom, and Meghir, 2012; Kinsler and Pavan, 2015). Beyond individual outcomes, the aggregate effect of students' major choices influences the supply of skilled workers and the overall skill composition, thereby affecting labor market dynamics, driving long-term changes in income inequality, and addressing or exacerbating skill shortages in key industries. While labor market characteristics influence college major choices, including factors such as expected wages, gender-biased beliefs, and information frictions, (Altonji, 1993; Gemici and Wiswall, 2014; Wiswall and Zafar, 2015; Altonji, Arcidiacono, and Maurel, 2016), less is known about the role of international trade and geopolitics.

In this paper, we study how trade tensions triggered by geopolitical conflicts and technological rivalry affect major choices in China using the U.S.-China trade war. From the Chinese perspective, on the one hand, rising U.S. tariffs decrease exports, a phenomenon we refer to as the export demand channel. This results in lower wages and fewer job opportunities among Chinese firms, which may diminish the attractiveness of majors related to affected industries. On the other hand, rising U.S. tariffs boost demand for skilled workers by increasing government support and firm investment in R&D, which we term the defensive innovation channel (Ju et al., 2024; Bai, Jin, and Lu, 2023). The trade war can serve as a catalyst for the government to prioritize technological self-reliance in key strategic sectors and greatly accelerated the government's push for domestic innovation. Chinese firms were incentivized to become more self-reliant by adopting new technologies and increasing R&D investment in response to significant threats to their supply chains. Both government industrial policies and corporate investments aimed at fostering defensive innovation send strong signals to the labor market, shaping students' career choices. Our empirical findings indicate that defensive innovation dominates the export demand channel. With higher wages and increased job opportunities for R&D occupations in high-tech industries, students were increasingly motivated to pursue science, technology, engineering, and mathematics (STEM) majors. This shift raised admission scores, particularly at elite universities, where graduates are better positioned for R&D-related roles.

In this paper, we make two contributions. First, we extend the body of research on international trade and educational attainment by exploring how trade policies shape students' major choices with granular college admission data. While many empirical studies show that educational attainment—e.g., college or no college—responds to increased job opportunities driven by trade liberalization (Atkin, 2016; Blanchard and Olney, 2017; Fan and Li, 2023), less is known about how trade influences students' college major choices. One exception is Smeets, Tian, and Traiberman (2024), who build a rich model of field choice with dynamic occupational choice using Danish data. Second, we highlight the unintended consequence of trade tensions on skill allocation by exploring a novel channel, namely defensive innovation. Trade disputes are often about technological rivalry and leading countries have incentives to influence foreign innovation through trade policies (Bai, Jin, and Lu, 2023). In the case of the U.S.-China trade war, China responded to higher trade barriers in the U.S. by reducing dependence on foreign technology, which drives talent into STEM-related fields. Our research highlights the pivotal role of trade policy in shaping the allocation of skills, emphasizing the mechanisms through which governments' industrial policies and firms' investment behavior influence labor market dynamics. These findings offer important implications for policymakers, educational institutions, and students, shedding light on how strategic policy decisions can steer human capital development and align educational choices with evolving industry demands.

Concretely, we examine the impact of the U.S.-China trade war on Chinese students' major choices using the National College Entrance Exam (NCEE), or *Gaokao*. The Gaokao aims to provide a standardized, uniform, and meritocratic benchmark for evaluating students. We use college admissions data from all Chinese higher education institutions from 2017 to 2020, which includes information on enrollment and admission scores, broken down by university, major, and students' provinces of origin.

Our identification strategy relies on an exposure design. The main independent variable is the province-major-level tariff shock. To construct this tariff exposure, we calculate the weighted tariffs faced by Chinese exporters, where the weights and tariffs vary by college major, province, and year. We map the original product-level tariffs imposed by all trade partners to province-major-level tariff exposure through three steps. First, we calculate province-product-level tariff exposure using the average product-level tariff weighted by the destination country-product-specific export shares of each province. Provinces with a larger share of a product's exports to U.S. will be more exposed to the tariff shock for that product. Second, we translate the province-product-level tariff exposure to the province-industry-level using the concordance from Pierce and Schott (2012), with the product-specific export shares in each industry of province as the weights. Third, we use American Community Survey (ACS) survey data on the employment distribution of workers with college degrees across various industries to convert the province-industry-level tariff exposure to province-major-level. Similarly, we construct province-major-level import tariffs to account for the effect of China's import tariffs on foreign products as a control.

We analyze the effects of tariff shocks at the province-major level on admission scores. The findings reveal that tariffs levied on Chinese exports increase admission scores for related majors.[1] Specifically, a 1 percentage point increase in average tariffs imposed across all trade partners can explain a 2% to 3% rise in standardized admission scores (with mean=0 and standard deviation=1). This means that, on average, a student would need to improve their rank by 393 positions (out of 140,329 NCEE participants per province-track annually).[2] More intriguingly, tariffs significantly impacted students at elite universities, particularly those at nationally elite institutions, with a lesser effect on local elite colleges and no noticeable effect on ordinary colleges. This suggests that trade shocks unexpectedly encouraged top Chinese students to choose majors subjected to tariffs. Additionally, we find that the increase in admission scores was primarily observed among STEM majors, while other fields, like economics, did not exhibit similar trends.

Several factors pose potential threats to our empirical identification. Specifically, Chi-

[1] Tariffs are constructed as the export-weighted tariffs across all Chinese trade partners, including but not limited to the U.S (Equation (1)). The variation in tariffs mainly comes from the U.S., as many countries only impose the most favoured nation (MFN) tariffs on Chinese exports which do not change much over time. Accordingly, the average weighted tariffs (Table A1 and Figure 2) are low and much smaller than the U.S. tariffs.

[2] There are three tracks in NCEE, including the liberal arts track, science track, and comprehensive track. Exams and enrollment quota are varied at province-track level. We will show more institutional details in Section 2.2.

nese students' major choices may have been influenced by industrial policies implemented prior to the trade war. Meanwhile, the U.S. tariffs may strategically target industries that received favorable treatment from the Chinese government before the trade war. To address this concern, we include major category-province-year fixed effects to account for the potential impact of each province's industrial policies on broad major categories. Additionally, our event study confirms the absence of pre-trends before the onset of the trade war. Furthermore, we exclude pilot cities of the "Made in China 2025", which is considered as the main industrial policy in China preceding the trade war. This exclusion helps isolate the effects of pre-trade war industrial policies from those directly attributable to the trade war, further demonstrating the robustness of our results.

The U.S. implemented export controls alongside import tariffs, and we further investigate the trade war's impact using export controls as an alternative measure. Chinese entities targeted by U.S. sanctions, along with their affiliates, have progressively reduced their dependence on U.S. technology, redirecting efforts toward bolstering domestic innovation.[3] We manually compile the export control entity list announced by the U.S. government, categorizing each item by industry and province. Using the crosswalk between industries and majors, we calculate province-major-level exposure to export control sanctions. Our findings reveal that, much like the effects of tariffs, admission scores increased for majors more exposed to export control sanctions. Notably, this effect is again observed only for STEM majors in elite universities. The robust results are intuitive, as the product coverage of export control highly overlaps that of the U.S. tariffs.

The U.S.'s punitive tariffs primarily targeted China's high-tech industries, which are closely linked to STEM disciplines. The main goal was to restrict the development of these industries in China and maintain the technological advantage of the U.S. by keeping Chinese firms out of the U.S. market. However, our results show that the trade war, in fact, attracted more top students to these majors rather than preventing talent from flowing into high-tech industries. There are several reasons for this phenomenon. First, the Chinese government responded to the tariffs by actively promoting domestic innovation in high-tech firms within STEM-related industries. This support included various forms of

[3] See Global Times news about Huawei launched "Young Geniuses" recruitment program to spur tech breakthroughs to response to U.S. trade ban. https://www.globaltimes.cn/page/202111/1240085.shtml

assistance, such as direct R&D subsidies and land rent discounts for firms affected by the trade conflict. Second, the tariffs and export control sanctions posed a significant threat to the supply chains of Chinese tech firms, prompting them to invest more in R&D to substitute for key foreign intermediates. Third, the increase in U.S. tariffs diminished the competitive advantage of Chinese firms based on low prices, compelling them to climb the quality ladder. Consequently, Chinese firms sought to offset these losses and maintain their competitiveness by improving efficiency and adopting new technologies. Generally, rather than retreating from these fields and acknowledging the dominance of U.S. tech giants, China chose to counteract these American policy measures through defensive innovation.

We investigate this proposed mechanism by using Chinese government subsidy data for publicly listed companies and firm job posting data to identify two main drivers shaping the major preferences of China's elite students: intensified government support for impacted industries and heightened corporate investment in innovation. First, we find that, following the onset of the trade war, the Chinese government substantially increased subsidies to targeted industries, aiming to bolster their development. Specifically, a 1 percentage point increase in weighted average tariffs on an industry led to a 7.99% increase in government subsidies to listed companies within that industry. This effect is observed not only for incumbent firms but also for start-ups, highlighting the Chinese government's proactive efforts to mitigate the negative impacts of U.S. tariffs on domestic industries.

Second, we use monthly job posting data from Chinese companies between 2017 and 2020 to investigate the dynamic impact of tariff shocks on occupational demand and average wages. Again, we apply the exposure design method to construct a prefecture-occupation-month-level tariff exposure measure based on the export share of prefectures and the distribution of occupations across various industries. Our analysis uncovers two novel insights. On one hand, U.S. tariff shocks generally led to a decline in average wages and job postings for affected non-R&D occupations, confirming the export demand channel. On the other hand, we find that companies significantly raised job postings for R&D occupations. R&D wages also increased relative to non-R&D occupations. This suggests that the defensive innovation channel dominates the export demand channel for skill-intensive occupations, companies are inclined to invest more in R&D to attract top talent and increase their competitiveness. Since R&D occupations often require advanced education and specialized skills, graduates from elite universities are likely better suited for these demands. This finding helps explain why trade war tariffs primarily increased admission scores for affected majors in national elite universities.

This paper contributes to three strands of literature, starting with the literature on trade and human capital accumulation. Previous studies have explored how export opportunities or import competition affects students' schooling decisions through changing labor market opportunities (Atkin, 2016; Greenland and Lopresti, 2016; Blanchard and Olney, 2017; Li, 2018; Khanna et al., 2023). Another body of research emphasizes that increased capital goods imports raise the skill premium (Burstein, Cravino, and Vogel, 2013; Parro, 2013; Fan, 2019), which encourages students to attend college (Fan and Li, 2023). Our analysis goes one step further and examines the impact of trade on major choices. By using novel and granular college admission data, we explore how college major admission scores respond to trade protectionism. Our paper is related to Smeets, Tian, and Traiberman (2024), who study the impact of labor market disruptions on students' major choices in a general equilibrium setting by endogenizing education choices. The two main differences are that we explore a different channel of defensive innovation and focus on the empirical analysis.

Second, we provide new insights into the growing literature on the economic impacts of trade protectionism. Previous studies have extensively analyzed the impact of U.S.-China trade war began in 2017 on trade flows and pass-through (Amiti, Redding, and Weinstein, 2019; Fajgelbaum et al., 2020; Jiao et al., 2022; Feng, Han, and Li, 2023; Fajgelbaum et al., 2024), economic growth (Chor and Li, 2024), economic resilience (Han et al., 2023), and wages and employment (Flaaen and Pierce, 2024; Benguria and Saffie, 2020; Goswami, 2020; Autor et al., 2024; He, Mau, and Xu, 2021). In this paper, we study the impact of the trade war on education decisions by providing empirical evidence on how Chinese skill supply responded to U.S. technological pressure. We find that tariff shocks paradoxically stimulated elite students to gravitate toward high-tech sectors. Our findings are consistent with previous findings that the U.S.'s objective in imposing tariffs was to undermine China's high-tech industries (Bai, Jin, and Lu, 2023; Ju et al., 2024). In response, Chinese companies sought to offset their losses by raising their R&D expenditures to improve efficiency and focus on high-value products (Li, Liu, and Yuan, 2022). Meanwhile, the U.S. tariffs also acted as a wake-up call for China to push for self-reliance in technology (Yang et al., 2022). Similar cases of trade protection spurring innovation and upgrading have been confirmed by Li, Li, and Yin (2024) who find that the EU's anti-dumping investigation into China's photovoltaic industry stimulated photovoltaic innovation and by Kim (2024) who observe that Japan's export controls on South Korea led to an increase in Korea's productivity and export.

Third, this paper contributes to the literature on the determinants of major choices. Previous research has explored how students form expectations about career prospects and potential earnings in specific majors and how these expectations shape their choices (Arcidiacono, Hotz, and Kang, 2012; Gemici and Wiswall, 2014; Wiswall and Zafar, 2015; Conlon, 2021). Specifically, Blom, Cadena, and Keys (2021) find that during recessions students tend to seek additional information and are more likely to pursue challenging majors. We underscore the role of geopolitics and government industrial policy in shaping college major choices.

The remainder of the paper is organized as follows. Section 2 introduces the background of our study. Section 3 describes the data and variables. Section 4 lays out the empirical strategy. Section 5 reports our main findings. Section 6 discusses our mechanisms. Section 7 concludes the paper.

2 Background

2.1 U.S. - China Trade War

2.1.1 The Cause of the U.S. - China Trade War

The U.S.-China trade war was sparked by competition over intellectual property and core technologies, with its origins tracing back to the "Section 301" investigation initiated by the U.S. government against China. In March 2018, the United States Trade Representative's Office released the report of the "Section 301" investigation, concluding that China's unfair practices concerning intellectual property and technology transfer had harmed American companies. Consequently, the U.S. imposed a 25% tariff on approximately $50 billion worth of Chinese imports, specifically targeting products from sectors regarded as "strategically" important and benefiting from China's industrial policies, while attempting to minimize impact on the U.S. economy.[4]

The U.S. government focused on high-tech products, despite their relatively low share of total imports (Ju et al., 2024; Bai, Jin, and Lu, 2023). By the end of 2018, the average tariff increase on high-tech sectors, including aircraft, optical instruments, electronic information technology, vehicles, and machinery, was 14.58%. U.S. punitive tariffs covered 72.08% of aircraft products, 73.41% of optical instruments, and 63.72% of machinery products,[5] while a large proportion of labor-intensive products, which account for a major part of China's exports to the U.S., remained almost unaffected. Feng, Han, and Li (2023) further highlighted a negative correlation between U.S. tariffs and imports from China, indicating that the underlying reason for the U.S. initiating the trade war was its deep concern over the rapid advancement of China's high-tech industry. The trade war is the result of a technological rivalry.

2.1.2 Chinese Responses, Public and Private

In response to the U.S. tariffs, China quickly implemented several rounds of retaliatory tariff measures, specifically targeting products such as agricultural goods and automobiles, which account for a high proportion of China's American imports. This strategy suggests that China aimed to pressure U.S. exporters in order to expedite the resolution of the trade war. Furthermore, the Chinese government introduced various policies to support industries affected by the trade war. For instance, land allocations were increased for high-tech sectors (Yang et al., 2022). Concurrently, government subsidies for companies in these impacted industries were also increased. As shown in Appendix Figure A1, the total

[4]See the Section 301 Fact Sheet at https://ustr.gov/about-us/policy-offices/press-office/fact-sheets/2018/june/section-301-investigation-fact-sheet

[5]The ratios are calculated based on import value. If we instead use the number of HS-8-digit product varieties, U.S. tariffs covered 97.73% of aircraft products, 83.42% of optical instruments, and 98.72% of machinery products.

government subsidies received by publicly listed companies in the high-tech manufacturing industry has increased significantly,[6] exceeding that of all other industries combined. This coincides with the timing of the U.S. 301 investigation, suggesting that the trade war catalyzed a shift in the Chinese government's industrial policy.

At the same time, Chinese companies have actively responded to U.S. technological suppression and trade sanctions. To ensure supply chain safety, many high-tech firms have increased their investment in R&D to substitute for key bottleneck technologies held by foreign firms. This included offering competitive salaries to attract top talent. For example, in June 2019, Huawei launched the "Young Geniuses" program, offering exceptional young talents salaries at least five times the national average, with a maximum annual salary of CNY 2 million (USD 284,814), to recruit the best innovators. Appendix Figure A2 illustrates that after the trade war began, the average wage for R&D positions surged, exemplified by occupations such as engineers. This evidence underscores the importance that companies place on technological innovation and reflects the determination of Chinese firms to strengthen their competitiveness through talent acquisition and technological innovation in the face of external pressures.

In conclusion, the U.S. - China trade war is not merely an economic and trade conflict. It is fundamentally a competition over talent, technology, and innovation. The defensive responses of the Chinese government and Chinese enterprises are part of China's current approach and long-term strategy in this broader competition.

2.2 College Enrollment and Major Choice in China

2.2.1 The National College Entrance Exam

The Gaokao, formally known as the National College Entrance Exam (NCEE), is conducted annually in June and is recognized as the nation's most important standardized exam in China. High school students from all provinces and regions take the NCEE simultaneously, and their scores determine college enrollment outcomes. Widely regarded as the

[6]The high-tech industries include Special Equipment Manufacturing, Instrument Manufacturing, Pharmaceutical Manufacturing, Transport Equipment Manufacturing, and Automobile Manufacturing.

first significant academic milestone, NCEE success facilitates admission into prestigious institutions promising lucrative career prospects and a fulfilling life.

The college enrollment process consists of three stages: exam, application, and university admission. While the Ministry of Education (MOE) of the central government establishes the primary principles and procedures of the NCEE, provincial administrations are responsible for its implementation, leading to variations in the details of the process across provinces.

The exam stage requires students to write the NCEE based on their chosen high school track, which includes the liberal arts track, science track, and comprehensive track. The NCEE comprises six subjects. Mathematics, Chinese, and English are mandatory for all tracks. Students on the liberal arts track are examined in history, geography, and political science, while those on the science track are tested in physics, chemistry, and biology. Comprehensive track students can select any three subjects from the aforementioned six. Most provinces only allow students to choose between the liberal arts and science tracks in the past. However, more and more provinces have recently opened up the comprehensive track for all students. Since exams are administered at the provincial level, scores are comparable only for students from the same year, province, and track.

2.2.2 Chinese University Applications and Admissions

The application and admission processes also occur at the provincial level based on students' NCEE scores and application lists.

First, students need to apply not only to universities but specific university-major combinations. Changing majors post-enrollment is very difficult. Only a limited number of universities permit students to change major, and the quota for such transfers is very low.[7] Chinese students thus exercise considerable caution when selecting "university-major" combinations, as their choices are closely related to their future career prospects.

Secondly, during the application and admission stages, the NCEE utilizes a "parallel

[7] According to data from the "Undergraduate Teaching Quality Report for the 2022-2023 Academic Year" covering over 160 universities in China, 72% of institutions recorded a major-switching rate below 1.25%.

mechanism" (Chen and Kesten, 2017; Bo et al., 2019), which is a hybrid of the Boston mechanism and deferred acceptance (Yang, 2024). This mechanism allows candidates to apply for a large number of equally treated "university-major" combinations, aiming to mitigate risks and avoid strategic application behavior. All universities are divided into several batches (typically 3 batches), The admission process run by order from the first batch to the third, corresponding to the best group of colleges to the lowest-ranked colleges. Typically, in each batch, students can select five universities and six majors per university, totaling 30 combinations.[8] Subsequently, a deferred acceptance algorithm is implemented at the college level to match colleges and students according to students' NCEE scores and application lists. Colleges then allocate admitted students into different majors using a Boston mechanism. Therefore, conditional on total enrollment, the final admission score cutoff serves as a reasonable measure of students' preferences.

Third, "university-major" enrollments are limited at the province level. Each year, universities formulate their enrollment plans, specifying the number of students to be admitted into each major. These plans require approval from the MOE. Following approval, universities distribute the total enrollment number for each major across provinces. This admission plan is released before students submit their applications, providing essential information for candidates' applications. The score of the last admitted student for a specific "university-major" combination serves as the cutoff admission score.

3 Data and Descriptive Analysis

3.1 College Enrollment Data

This paper employs enrollment data from the NCEE spanning 2017 to 2020, collected from official college application guidance documents across all provinces. The dataset includes admission statistics across different majors at 1,266 undergraduate institutions in 31 provinces of mainland China. It encompasses information on the actual number of

[8] The detailed application rules differ across provinces and years. Some provinces allow more than 30 combinations.

enrolled students, admission cutoff scores, and cutoff provincial rankings for each college-major combination in each province. Origin observations are at the *college-major-province-track-year* level. In this setting, province means the applicant's province of residence. Table 1 presents an overview of the admission statistics by college.

Among the 1,271 undergraduate institutions, significant variations exist in educational quality. There are 118 national elite universities, 253 regional elite universities, and 898 ordinary universities, constituting approximately 9%, 20%, and 71% of all universities in China, respectively. National elite universities refer to institutions designated by the "211 Project". These universities are typically supervised by the national MOE and boast extensive histories and esteemed reputations. Local elite universities, or *shuangfei yiben*, on the other hand, are usually overseen by provincial education authorities and enjoy significant recognition within their respective provinces and neighboring regions, albeit with educational standards lower than those of national elite universities. Typically, national elite universities and local universities compose the first batch of universities. Ordinary universities encompass all other higher education institutions (part of the second batch and part of the third batch of universities). As depicted in Table 1, Panel A, the ordinary university admits an average of 1,729 new students across 26 majors annually. Elite universities, due to their larger scale, tend to enroll a greater number of students. Furthermore, owing to their national renown, elite universities often attract applicants from a broader spectrum of provinces.

Panel B in Table 1 reveals a large gap between cutoff scores for colleges at different levels. The average score for admission to national elite universities is 583.85 (93rd percentile), surpassing the ordinary colleges by 118.01 points (63rd percentile), which means on average, only the top 7% of all applicants can get into the national elite universities. Another notable observation is the substantial disparities in admission cutoff scores across different majors even within national elite universities, with a standard deviation of 65.89. This underscores the fierce competition students face in selecting majors, where only those with higher scores can secure admission to popular programs.

Table 1 Descriptive Statistics

Panel A	Enrollment Number		Number of Majors		Enrollment Provinces		Observations	
college	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	N	Share
Nation Elite College	2985.17	1901.09	42.59	21.65	28.84	2.89	471	9.66%
Local Elite College	3180.69	1880.78	44.52	18.50	26.22	5.84	990	20.29%
Ordinary College	1729.45	1368.81	26.49	14.13	18.03	8.27	3417	70.05%
Panel B	Admission Score		Admission Percentile		Enrollment Number		Observations	
College-Province-Major	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	N	Share
Nation Elite College	583.85	65.89	0.93	0.09	5.34	13.82	263308	19.89%
Local Elite College	521.87	62.73	0.80	0.14	7.07	21.31	445247	33.65%
Ordinary College	465.84	64.47	0.63	0.19	9,61	24.98	614821	46.46%

Notes: Panel A presents college-level admissions data from 2017 to 2020, including the total number of students admitted nationwide each year, the number of majors offered, and the number of provinces (out of 31) from which the college enrolls students. Panel B provides average annual admissions data at the college-province-major level, including the average admission score for each major, the average provincial ranking of admission scores, and the average number of students admitted per year. *Source:* Admissions guidebooks issued by the provincial educational admissions authorities.

3.2 Tariff and Trade Data

This section details the process of gathering tariff and trade data, as well as the construction of the key explanatory variable: the tariff exposure specific to each province-major, which is constructed from product-level tariffs.

3.2.1 Tariff Data

We collected tariff data from three sources to construct a monthly panel dataset of export and import tariffs in China during the U.S.-China trade war from 2017 to 2020.

First, we consider the monthly *tariffs faced by Chinese products* exported to the U.S. During the U.S.-China trade dispute, the effective tax rate for Chinese exports to the U.S. was determined by two key pieces of information: (1) the HS8 product-level baseline tariff schedule, released each January and mid-year by the United States International Trade Commission (USITC), and (2) the HS10 product-level punitive tariffs and tariff exemptions imposed on Chinese exports to the U.S., based on United States Trade Representative (USTR) announcements. When calculating the tariffs, we sum the baseline and punitive tariffs if the product is not on the tariff exemption list. Conversely, if a product is included in the exemption list, the tariff applied is the annual baseline tariff. Using the implementation dates of punitive tariffs and tariff exemptions, we measure all tariffs at the monthly level.[9] To match the HS6 Chinese customs data, we take the simple average of all associated HS10 or HS8 product tariffs to construct the monthly HS6 product tariff panel data.

Second, we consider the monthly *import tariffs imposed on Chinese imports of American products*. During the U.S.-China trade war, the Chinese government implemented multiple rounds of retaliatory tariffs. To determine the actual tax rate on Chinese imports from the United States, two key factors need to be considered: the annually released HS10 product-level baseline tariff schedule by the General Administration of Customs China and the HS8 product-level retaliatory tariffs and tariff exemptions imposed on Chinese imports from the U.S. by the Ministry of Finance of China. We apply the same calculation method used for the U.S. tariffs and standardize the import tariffs of products to the HS-6 monthly level by taking averages.

Finally, we also consider the *tariffs faced by Chinese products exported to other countries and the tariffs imposed on products imported from other countries*. Although the United States is one of China's most significant trade partners, the importance of other countries as China's trading partners should not be neglected. To accurately measure the applied tariffs, we collected HS6 product level tariffs for Chinese exports to other countries from the United Nations Conference on Trade and Development (UNCTAD) database. Additionally, we manually collected data on country-specific HS8 product-level import tariff adjustments from the MFN tariff schedule and Free Trade Agreement (FTA) preferential rates released by the Ministry of Finance of China. We then averaged these tariffs to the HS-6 product monthly level. Throughout the sample period, China reduced its MFN tariffs and preferential tariffs multiple times.

3.2.2 Trade Data

We draw on the import and export data from China's General Administration of Customs to construct the weights in calculating each major's exposure to the tariffs. This dataset records every transaction made by Chinese enterprises, encompassing the HS8

[9] If the punitive tariff was implemented in the middle of the month, we scale the tariff by the number of days of the month it was in effect, following Fajgelbaum et al. (2020).

product code, product value, product quantity, and import source (or export destination) country. To align with the tariff data, we aggregate the transaction data to the HS6 product level. In 2017, this import and export trade data includes detailed information on 5,022 HS6 products imported from 235 source countries and 5,007 HS6 products exported to 237 destination countries.

3.2.3 Construction of Trade Exposure

In this section, we illustrate the procedure to map the *original product-level tariff on Chinese products* to *province-major level tariff exposure*, which is our main independent variable. Figure 1 depicts the construction method.

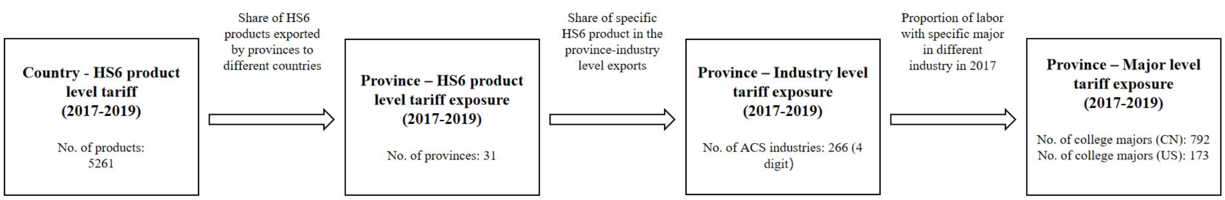

Figure 1 Method for Calculating Province-Major Tariff Exposure

The impact of tariffs on specific province-major combinations varies for two main reasons. First, the impact of tariffs differs across provinces. When the U.S. imposes punitive tariffs on Chinese products, the effect varies according to the export product share and export destination share of each province. Provinces with fewer exports to the U.S. relative to their total exports, or provinces with smaller export shares of target products by the tariff, experience a smaller impact. Second, the effect of tariff shocks differs for workers from different industries, and thus, with different majors. As previously mentioned, college major is closely linked to future industry affiliation (see Appendix Table A2). Therefore, we adopt an exposure design approach to calculate the tariff shocks at the province-major level.

In the first step, we calculate the average tariff at the HS6 product level for each province by averaging the original tariffs imposed by all destination countries based on the export shares of each province in 2017.

$$Tariff_{pkt} = \sum_{c} \frac{Export_{pck,2017}}{Export_{pk,2017}} \times Tariff_{ckt} \tag{1}$$

c, p, k, t represent the export destination country, Chinese province, HS6 product, and time, respectively. $Tariff_{ckt}$ is the tariff imposed by destination country c on product k from China in time t. $Export_{pck,2017}$ is the total export value of product k from province p to country c in 2017 before the trade war. $\frac{Export_{pck,2017}}{Export_{pk,2017}}$ is the share of product k from province p sold to country c in 2017.

In the second step, we aggregate the tariff from the province-HS6 product level to the province-industry level, based on the correspondence between industries and products and the export share of each HS6 product within each industry. We use the concordance from Pierce and Schott (2012) to map HS6 products to NAICS6 industries:

$$Tariff_{pjt} = \sum_{k \in j} \frac{\frac{1}{N_k} Export_{pk,2017}}{Export_{pj,2017}} \times Tariff_{pkt} \tag{2}$$

p, j, k, t denote the province, industry, HS6 product, and time, respectively. $Tariff_{pkt}$ is the tariff exposure at province-HS6 level derived from the first step. $Export_{pk,2017}$ represents the aggregate export value of product k originating from province p in 2017. In cases where an HS6 product is associated with multiple industries, we distribute its export value evenly across those N_k industries. Thus, we multiply the tariff of product k with an exposure term $\frac{\frac{1}{N_k} Export_{pk,2017}}{Export_{pj,2017}}$ which evaluates the share of product k in industry j.[10] Then, we use the official code list of the American Community Survey to map NAICS6 industries to ACS industries to complete the second step.[11]

In the final step, using the ACS data on the employment distribution of workers with college degrees across various industries, we calculate the tariff shocks at the province-

[10]In fact, few HS6 products are linked to multiple industries, as 92% of 5,261 HS6 products are uniquely attributed to a single industry.

[11]The major-industry mapping data is not available in China.

major level by a weighted sum of the tariff shock for each province-industry combination.

$$Tariff_{pmt} = \sum_j Weight_{jm,2017} \times Tariff_{pjt} \tag{3}$$

$$Weight_{jm,2017} = \frac{Employ_{jm,2017}}{\sum_j Employ_{jm,2017}} \tag{4}$$

$Tariff_{pjt}$ is the province-ACS industry level tariff exposure calculated from the second step. $Weight_{jm,2017}$ is the proportion of workers with major m employed in industry j during the baseline year of 2017. Specifically, the numerator $Employ_{jm,2017}$ denotes the number of individuals with major m working in industry j according to the ACS data. The denominator $\sum_j Employ_{jm,2017}$ represents the total number of individuals with major m employed across all industries. It is worth noting that the ACS data is based on American degree classification, and there are differences between university systems in the United States and China. We manually match and construct a correspondence table between Chinese and American university majors, which allows us to calculate the tariff shocks at the province-Chinese major level. To control for the impact of China's retaliatory tariffs, we use the same calculation method to estimate the weighted average Chinese import tariff shocks faced by each province-major combination.

3.3 U.S. Entity List Data

During the U.S.-China trade war, in addition to punitive tariffs, the U.S. implemented export controls based on what is officially termed the Entity List of the Export Administration Regulations (Entity List). The Entity List, as specified in Supplement No. 4 to Part 744 of the U.S. Export Administration Regulations (EAR), was first published by the Bureau of Industry and Security (BIS) under the U.S. Department of Commerce in February 1997.[12] Since its initial publication, grounds for inclusion on the Entity List have expanded to activities sanctioned by the State Department and activities contrary to U.S. national security and/or foreign policy interests. According to regulations, U.S. exporters conducting

[12]See the Entity list in Supplement No. 4 to Part 744 of the Export Administration Regulations (EAR) (15 C.F.R. Part 744, Supp. No. 4) https://www.bis.doc.gov/index.php/policy-guidance/lists-of-parties-of-concern/entity-list

transactions—including exports, re-exports, or domestic transfers—with entities on the list are subject to stringent requirements and policies. Inclusion on the entity list often results in entities being severed from international upstream suppliers or experiencing significant disruption to ongoing and planned R&D activities.

From 2017 to 2020, a total of 437 Chinese high-tech enterprises and research institutions, including Huawei, Hikvision, and China Aerospace Science and Industry Corporation, were added to the U.S. Entity List. Using the entity names, addresses, and other details posted by BIS, we matched these entities to China's business registration records to identify their corresponding industries. This allows us to construct a province-industry-month-level panel dataset of Entity List inclusion shocks, which we use to develop an alternative measure of U.S.-China technological competition.

3.4 Job Posting and Wage Data

We also utilize online job posting data to investigate the impact of the trade war on labor demand for different occupations. The dataset includes approximately 1.2 billion recruitment entries posted on major Chinese online recruitment platforms from 2017 to 2020. These platforms, which include Zhaopin, 51job, 58.com, Ganji, Lagou, and Liepin, are the most popular in China, encompassing the vast majority of online job listings and providing us with the most comprehensive real-time labor demand dataset available.

We source the raw data through web scraping and meticulously refine it to eliminate duplicates and irrelevant entries. The cleaned dataset includes detailed information on job postings, such as the number of positions available, job titles, job descriptions, company names and profiles, job locations, posting dates, and wages. This data is aggregated by month.

3.5 Descriptive Analysis

3.5.1 Trade Exposure across Majors

Figure 2 illustrates the impact of tariff shocks on various major disciplines in China. The tariff shocks are defined by differencing tariffs between Dec. 2019 and Dec. 2017. The weighted average tariffs (blue boxes) are most linked to engineering majors, particularly in fields such as high-end manufacturing and electronic information technology, reflecting that American tariffs were mostly applied on China's high-end manufacturing industries. As discussed in Ju et al. (2024); Bai, Jin, and Lu (2023), the U.S. strategically employs tariffs as a tool to suppress the development of high-tech industries in China. Conversely, agricultural majors face the highest weighted average Chinese tariffs (red boxes), reflecting the substantial retaliatory tariffs imposed by China on U.S. agricultural products. In the following analysis, we use the foreign tariffs imposed on Chinese products as the main regressor (named "Tariff") and take the Chinese tariffs on foreign products as a control (named "Chinese Tariff").

3.5.2 The Flow of Talents in China

Before the detailed regression analysis, we present preliminary evidence on the effect of tariff shocks on students' major choices. We draw a bin scatter plot (each dot includes various province-college-major observations) in Figure 3 and illustrates the positive correlation between changes in tariff exposure for majors and changes in admission scores. Majors that experienced larger tariff increases from 2017 to 2019 (predominantly STEM majors, as shown in Figure 2) also saw higher increases in admission scores. This rise in scores indicates intensified competition for these majors, reflecting students' growing willingness to pursue fields aligned with the country's strategic priorities.

Notably, points at the far right of the figure are STEM-related, corresponding to the majors with the highest tariff exposure and largest admission score increases (as shown in Table A3). In particular, they are concentrated in fields such as mechanical engineering, material sciences, and electronic information. We will examine this positive relation and the mechanism in more details in the following sections.

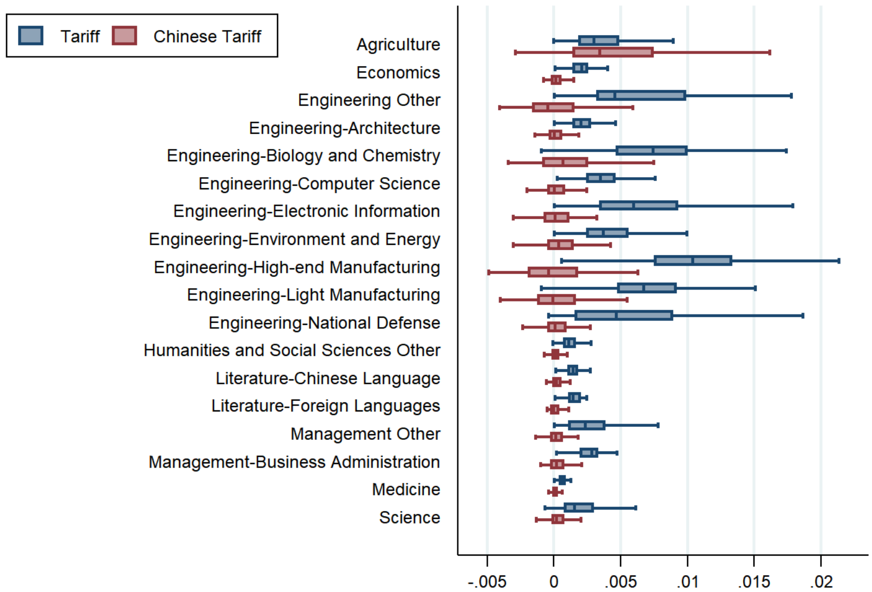

Figure 2 Tariff Shock on Disciplines in 2017-2019

Notes: This figure illustrates the changes in tariff exposure across different disciplines from 2017 to 2019. The blue boxes indicate the average tariffs exposure of disciplines. We convert the original product-level tariff across all recipients of Chinese exports to the province-major level according to equation (1)-(3) and take an average for all majors in the same discipline. The red boxes represent the average Chinese tariff exposure of disciplines, which covert from product-level Chinese import tariff on foreign products across all trade partner. Engineering discipline has been categorized into High-end manufacturing, Light manufacturing, Electronic information, Computer science, Biology and Chemistry, Environment and Energy, National defense, Architecture, and other engineering majors, as there are 269 majors in engineering discipline, accounting for 34% of Chinese college majors. Humanities and Social Sciences Other, represent a collection of majors in History, Philosophy, Art, Law, and Education disciplines.

Source: Tariff data from the Customs General Administration of China, the United States Census Bureau, the United States Trade Representative (USTR), the WITS tariff dataset, and the United States International Trade Commission (USITC); employment data from the ACS.

4 Econometric Specification

In our main regression, we investigate how the tariff shocks from the U.S.-China trade war affect college students' choices of major. We estimate the following empirical model:

$$\begin{aligned} NCEE\_Score_{ipsmt} = & \alpha + \beta_1 Tariff_{pm,t-1} + \beta_2 CHN\_Tariff_{pm,t-1} \\ & + \gamma NumAdm_{ipsbmt} + \delta_{pst} + \mu_{m'pt} + \xi_{ipbt} + \varepsilon_{ipsmt} \end{aligned} \tag{5}$$

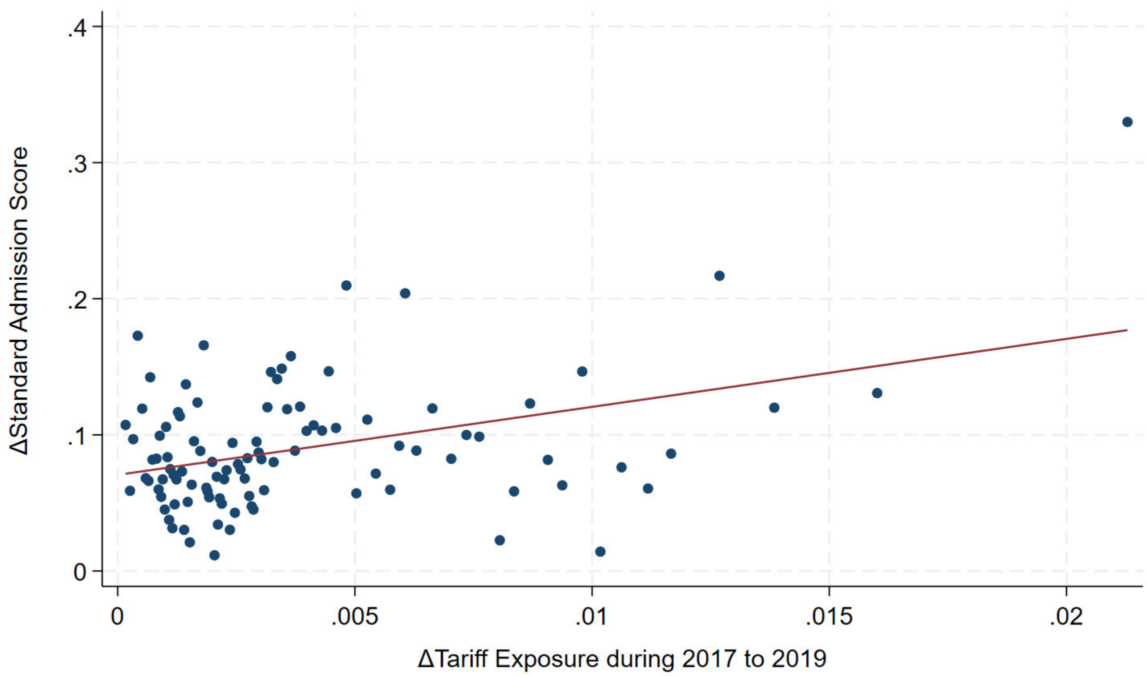

Figure 3 Tariff Exposure and Admission Score

Notes: This figure shows a binned scatter plot for the relation between the change in tariff exposure and the change in standardized admission score by major during the U.S.-China trade war. The horizontal axis represents the change in tariff exposure at the province-major level from 2017 to 2019. The vertical axis represents the change in standardized admission scores from 2018-2020 at the province-college-track-major level. High school in China is typically divided between liberal arts, science, and comprehensive tracks.

Source: Tariff data from the Customs General Administration of China, the United States Census Bureau, the United States Trade Representative (USTR), the WITS tariff dataset, and the United States International Trade Commission (USITC); Employment data from the ACS; The university enrollment data from official application guidance documents across various provinces.

i, p, s, m, t denote the college, applicant's province, NCEE track, major, and time, respectively. $NCEE\_Score_{ipsmt}$ denotes the standardized admission score cutoff (calculated within province-year-track clusters) for major m, university i, in applicant's province p, track s, and year t. The mean is zero and the standard deviation is one. This is the minimum score required for admission to the university-major pair in a specific province in that year. This cutoff score partly reflects student preferences—the more students apply for a major, the higher its "price," that is, the higher the admission score. $Tariff_{pm,t-1}$ represents the province-major level average tariffs on Chinese exports in the previous year. As the application stage of NCEE is around July each year, and it takes time for tariff shocks to impact households and students, we use the tariff rates from December of the previous year as the core explanatory variable. In addition, we control for the weighted average import tariffs across all trade partners imposed by the Chinese government (mainly retaliatory tariffs on the U.S.) $CHN\_Tariff_{pm,t-1}$. We further control for the enrollment of the university-major combination for a specific province in a given year, $NumAdm_{ipsmt}$, to control for the impact of education supply changes.

Due to the high dimensionality of the dependent variable, variations in admission scores may arise from other confounding sources. We include several fixed effects in equation (5) to control for province-track-year, major category-province-year, and college-province-batch-year shocks. First, because admission scores differ across geographical locations, tracks (liberal arts, science, or comprehensive tracks), and years, we include province-track-year fixed effects δ_{pst} for comparability. Second, there could be a pre-existing trend where STEM majors are becoming more popular relative to arts majors in China, or in some specific provinces. We control for major category-province-year fixed effects $\mu_{m'pt}$ to account for preference shocks to certain major categories within particular provinces and the potential impact of each province's industrial policies on broad major categories.[13] In addition, the major category-province-year fixed effects also address the concern that the U.S. tariffs may strategically target industries that received policy support from the Chinese government before the trade war. Third, as university enrollment is conducted in different batches, we include college-province-batch-year fixed effects ξ_{ipbt} to account for the enrollment arrangements of colleges in different province-batches, such as total enrollment and major allocation. This set of fixed effects can also capture the reputation of colleges in different regions. In all regressions, standard errors are clustered at the college level to account for the potential correlation over time and across provinces. Each observation of the admission score cutoff is weighted by the number of students admitted.

[13]For example, Tesla's construction of a vehicle factory in Shanghai could affect local demand for labor in engineering majors or the major tastes of local students.

5 Main Results

5.1 Baseline Result

Table 2 displays the positive impact of higher tariff exposure on college admission scores. For clarity, we denote the weighted average tariffs from all trade partners levied on Chinese exports as "Tariff" in all regression tables. The Chinese weighted average tariff on import products from other countries is included as a control variable. From column (1) to (4), we include different sets of fixed effects and the results are robust. As shown in Table 2 column (1), higher tariffs imposed by trade partners, mainly the U.S., on Chinese exports have notably elevated the admission scores of related majors. This suggests that majors more adversely affected by tariffs have become more popular among students. In general, we find that a one percentage point (1.68 percent of standard deviation) increase in the weighted average tariff imposed by all trade partners on China leads to a 2-3 percentage points increase in standardized admission score (with mean=0 and standard deviation=1). The results are unchanged if we construct the tariff shock only considering tariffs between the U.S. and China, as shown in Appendix Section B.4.

The main results are surprising at first glance. As one of the goals of the U.S. trade war was to curb the advancement of China's high-tech industries, one would expect that these industries became less attractive to skilled labor. Consequently, majors related to these industries would become less popular. However, this was not the case during the U.S.-China trade war. We observe that the tariff shock made majors associated with targeted high-tech industries more popular, leading to a greater influx of talent.

This suggests that, in terms of human capital investment, the tariff shock did not successfully impede the development of China's high-tech industries. We attribute this to defensive innovation. In response to the tariff shock, both the Chinese government and private firms ramped up their investment in critical technologies. This has seemingly offset the expected decline in labor demand and wages intended by the tariff shock. Instead, the affected fields gained more public attention and popularity. In the following sections, we will present more evidence supporting this mechanism.

Table 2 Baseline Results

Variables	Standardized Admission Score			
	(1)	(2)	(3)	(4)
Tariff	2.885***	2.842***	2.915***	2.134***
	(0.698)	(0.640)	(0.635)	(0.428)
Controls	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y	Y
College-Province FE	Y	Y	N	N
College-Year FE	N	Y	N	N
College-Province-Year FE	N	N	Y	N
College-Province-Batch-Year FE	N	N	N	Y
Observations	918,010	918,010	918,010	918,010
R-squared	0.923	0.927	0.931	0.968

Notes: This table reports the results of the main regression. The dependent variable is standardized admission scores at the college-province-track-major-year level. The independent variable is the weighted average tariff across all buyers of Chinese exports at the province-major-year level. The sample covers the years 2017 to 2020. All regressions are weighted by total enrollment at the province-college-track-major level. We control for province-track-year fixed effects and major category-province-year fixed effects in all columns. In column (1), we further control for college-province fixed effects. In column (2), we additionally control for college-province and college-year fixed effects. In column (3), we add college-province-year fixed effects. In column (4), we further control for college-province-batch-year fixed effects. The province-major-year level average Chinese tariff on foreign imported products and province-college-track-major level enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2 Evidence from Event Study

A key threat to our identification strategy is the potential endogeneity of tariffs. U.S. tariffs may reflect an endogenous response to China's export patterns or pre-trade war industrial policies, which could have already influenced Chinese students' major choices before the trade war. To address this concern, we use an event study regression to visualize the effect of tariff exposure on college admission scores. The tariff increase from June 2017 to December 2019 serves as a continuous treatment measure, with 2018 designated as the treatment year. The regression is specified as follows:

$$
\begin{aligned}
NCEE\_Score_{ipsmt} = \alpha &+ \sum_{q=-2}^{4} \beta_q I(event_q) \times \Delta Tariff_{pm} \\
&+ \sum_{q=-2}^{4} \gamma_q I(event_q) \times \Delta CHN\_Tariff_{pm} + \theta NumAdm_{ipsbmt} \\
&+ \delta_{ps} + \xi_{ip} + \mu_{m't} + \varepsilon_{ipsbmt}
\end{aligned} \tag{6}
$$

$NCEE\_Score_{ipsmt}$ denotes the standardized admission score cutoff (calculated within province-year-track clusters) for major m, university i, in applicant's province p, track s, and year t. $\Delta Tariff_{pm}$ represents the province-major level tariff surge in Dec. 2019 relative to that of Dec. 2017, and ΔCHN_Tariff_{pm} represents province-major level Chinese tariff change. The dynamic specification covers an event window spanning 2 years before and 4 years after the initiation of the US-China trade war. The indicators $I(event_q)$ are a set of year dummies in the event window. We use 2018 as the baseline year. The estimated vectors of β_q reveal the correlation between tariff shock during U.S.-China trade war and the college admission score in each year. In addition, we control for province-track, province-college, and major category-year fixed effects and province-college-track-major level enrollment.

Figure 4 shows no discernible pre-trends in college admission scores prior to the U.S.-China trade war, supporting our assumption that, before the trade war, admission scores for majors with different levels of tariff exposure did not differ significantly. However, following the onset of trade friction between the U.S. and China in 2018, standardized admission scores for majors more exposed to tariff shocks increased significantly, with the positive effect intensifying in subsequent years.

5.3 Elite and Non-elite Colleges

For the same field of study, the average career trajectory of elite college graduates can differ substantially from graduates of other colleges. Students from elite colleges tend to possess superior professional skills and greater innovative capabilities than their peers from non-elite colleges, and on average be more likely to contribute to innovation and de-

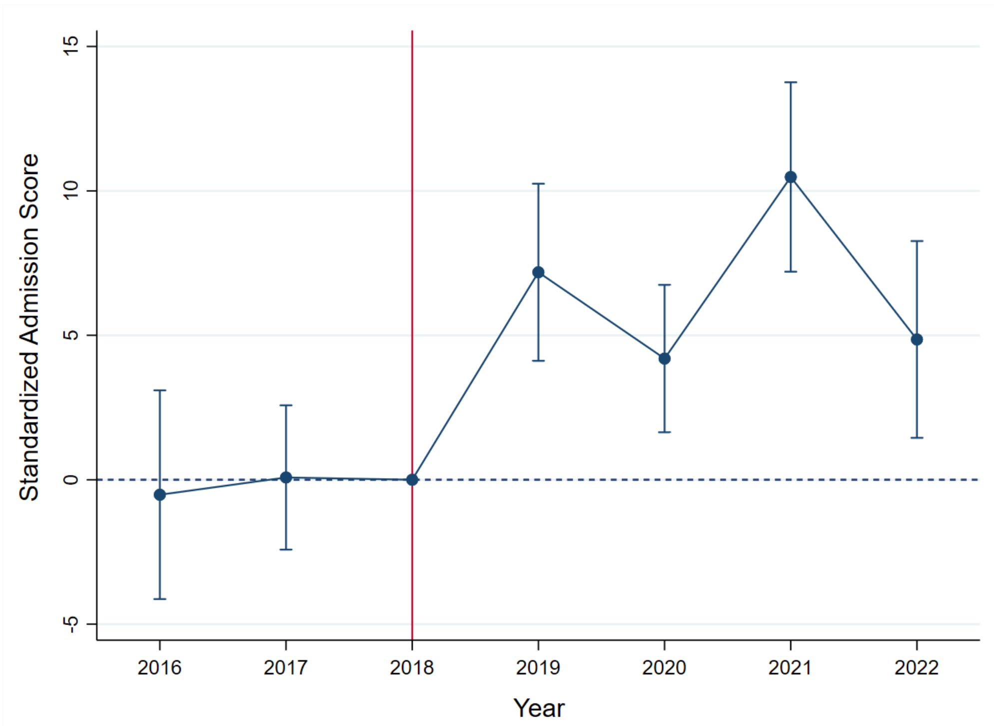

Figure 4 Event Study of Tariff Effect on Admission Score

Notes: This event study shows the annual effect of tariff shock on college admission score. We use the province-major level tariff surge in Dec. 2019 relative to that of Dec. 2017 as continuous treatment variable, and the college-province-track-major-year level standardized admission scores as dependent variable. Coefficients are estimated for each year from 2016 to 2022, using a dynamic difference-in-difference design. We use 2018 as baseline for comparison. We control for province-track, province-college, and major category-year fixed effects. The province-college-track-major level enrollment and the interactions between Chinese tariff increase and each year dummies are included as control variables. All estimates include 95% confidence intervals, where standard errors are clustered at the college level.

Source: Tariff data from the Customs General Administration of China, the United States Census Bureau, the United States Trade Representative (USTR), the WITS tariff dataset, and the United States International Trade Commission (USITC); The university enrollment data from official application guidance documents across various provinces.

velopment. As the defensive innovation channel is expected to mainly affect skill-intensive occupations, we would expect the tariffs to hit R&D related skill-intensive occupations more and thus have a larger impact on elite colleges.

We investigate the heterogeneity between elite and non-elite colleges in Table 3. We include interaction terms between the tariff shock and *National Elite* (column 2), *Local Elite* (column 3), and both (column 4). *National Elite* indicates whether a university is sponsored by the 211 Project, and *Local Elite* denotes whether a university is part of the first batch of universities but not sponsored by the 211 Project. Table 3 shows that the positive effect of higher tariffs on admission scores is mainly driven by elite colleges. In all cases, we observe that the positive effect of tariff exposure is most pronounced for students applying to national elite colleges, weaker for local elite colleges, and non-existent for regular colleges. A one percentage point increase in tariff exposure leads to a 6.16 percentage increase in the standardized admission score in national elite colleges and 2.39 percentage in local elite colleges.

5.4 STEM and Non-STEM Majors

As shown in Figure 2, the STEM majors are most affected by the tariff. If the main goal of U.S. punitive tariffs was to contain Chinese high-tech industries, we should observe the impact to be more pronounced for STEM majors than non-STEM ones. We test this conjecture by running our main regression on different major groups. Table 4 shows that only the admission scores of STEM majors in national elite universities (Engineering & Science) were significantly increased by the tariffs (columns 1 and 2). This suggests that U.S. tariffs stimulated an influx of talented students into STEM majors at elite universities. This result supports the defensive innovation channel, suggesting that the impact is likely to be most pronounced in elite universities, whose graduates are anticipated to take a leading role in driving innovation.

Columns (3)-(6) in Table 4 show that the increased tariffs have no significant effect on the admission scores of non-STEM majors in national elite colleges. For management, economics, and literature majors, the tariff shock pulled down admission scores for regular

Table 3 Tariff Exposure and Admission Scores Across College Types

Admission Score	(1)	(2)	(3)	(4)
Tariff	2.134***	1.366***	1.961***	0.583
	(0.428)	(0.429)	(0.496)	(0.497)
Tariff × National Elite		4.801***		5.578***
		(0.794)		(0.825)
Tariff × Local Elite			0.491	1.802***
			(0.660)	(0.662)
Controls	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y	Y
Observations	918,010	918,010	918,010	918,010
R-squared	0.968	0.968	0.968	0.968

Notes: This table reports estimates of the heterogeneous effects of tariffs on admission scores across different college types. The dependent variable is standardized admission scores at the college-province-track-major-year level. The independent variable is the weighted average tariff across all buyers of Chinese exports at the province-major-year level, and its interaction terms with a college type dummy. National elite colleges refer to universities sponsored by the 211 Project, which roughly corresponds to the top 100 universities in China. Local elite colleges refer to universities in the first batch of the admissions process but not sponsored by the 211 Project. The sample spans the years 2017 to 2020. All regressions are weighted by total enrollment at the province-college-track-major level. We control for province-track-year fixed effects, major category-province-year fixed effects, and college-province-batch-year fixed effects in all columns. The province-major-year level Chinese tariff on foreign imported products (and its interactions with elite university dummies) and province-college-track-major level enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

colleges. Since college graduates in these majors have a broader range of career choices compared to science and engineering majors, we infer that the negative effects in non-STEM majors capture the aggregate demand shocks caused by the tariffs.

Table 4 Tariffs and Admission Scores Across Major Categories

Admission Score	(1) Engineering	(2) Science	(3) Management	(4) Economics	(5) Literature	(6) Agriculture
Tariff × National Elite	2.622***	8.747**	-2.528	11.292	26.818	0.499
	(0.778)	(4.333)	(3.771)	(35.736)	(19.091)	(1.276)
Tariff	-0.242	0.886	-3.236***	-20.518*	-22.165***	1.644**
	(0.391)	(1.994)	(0.998)	(11.534)	(6.325)	(0.806)
Controls	Y	Y	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y	Y	Y	Y
Observations	346,128	63,706	170,751	58,137	96,996	16,108
R-squared	0.978	0.975	0.967	0.982	0.974	0.979

Notes: This table reports estimates of the heterogeneous effects of tariffs on admission scores across different major categories. The dependent variable is standardized admission scores at the college-province-track-major-year level. The independent variable is the weighted average tariff across all buyers of Chinese exports at the province-major-year level, and its interaction term with the national elite college dummy variable. We run the regression separately for different major categories. Major categories with fewer than 10,000 observations are excluded from the table, including philosophy, history, and art. Medicine is also excluded because its tariff exposure is too small (mean value 0.0017, see figure 2). The sample spans the years 2017 to 2020. All regressions are weighted by total enrollment at the province-college-track-major level. We control for province-track-year fixed effects and college-province-batch-year fixed effects in all columns. The province-major-year level Chinese tariff on foreign imported products (and its interactions with elite university dummies) and province-college-track-major level enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.5 Alternative Measure: U.S. Export Controls

Beyond punitive tariffs, the U.S. implemented export controls on some Chinese firms and institutions using the entity list. To further alleviate concerns that tariffs may not adequately represent U.S.-China technological rivalry, we employ U.S. export control intensity as an alternative measure. We begin by calculating the effective export controls at the province-industry level and then aggregate to the province-major level weighted by the employment share of specific major graduates across various industries. The calculation of export control intensity at the province-industry level is defined as follows:

$$Export\_control_{pjt} = \sum_{i \in j} Y_{pijt} \tag{7}$$

i, j, t denote firm (on the entity list), industry, and year. Y_{pijt} is a dummy variable representing whether Chinese firm i in industry j was designated on the U.S. entity list in year t. Considering that larger firms have greater influence within their industries, we also replace Y_{pijt} with firm registered capital or number of employees, thereby capturing heterogeneity in firm size. Then, we map the export controls from the province-industry level to the province-major level.

$$Export\_control_{pmt} = \sum_{j} Weight_{jm,2017} \times Export\_control_{pjt} \tag{8}$$

$$Weight_{jm,2017} = \frac{Employ_{jm,2017}}{\sum_j Employ_{jm,2017}} \tag{9}$$

Consistent with equation (4), the variable $Weight_{jm,2017}$ captures the relationship between the majors obtained by workers and the industries in which they are employed. $Employ_{jm,2017}$ denotes the number of individuals with major m engaging in industry j according to the ACS. The mean of this province-major level export control exposure measure (without weighting by registered capital or employee) is 0.037 in 2019. That is, a student in the job market will averagely encounter 0.037 firms being included in the entity list related to his/her major.

Table 5 presents the results using export controls as the measure of U.S.-China technological rivalry. Columns (1)–(3) respectively utilize the total number of firms on the entity list, the aggregated registered capital of these firms, and their total number of employees to quantify the intensity of export controls in specific industries. Stronger export controls significantly increase admission scores for related majors, which aligns closely with the impact observed for tariffs. For each additional firm related to major m in province p on the entity list, the cutoff admission score for that major increases by 3.6 percentage points. Meanwhile, we observe that the impact of the tariff is persistent when we additionally consider the export control.

We further extend the model by incorporating interaction terms between export limits and two categories of elite universities. The results in column (4) of Table 6 show that U.S. export controls raise admission scores only for related majors at elite universities, with a stronger positive effect observed for national elite universities.

Table 5 Alternative Measure: Export Controls

	Standardized Admission Score		
VARIABLES	(1)	(2)	(3)
Export Control	0.036*		
	(0.019)		
Export Control (Asset)		0.004***	
		(0.001)	
Export Control (Employee)			0.012***
			(0.002)
Tariff	2.018***	1.921***	1.712***
	(0.426)	(0.424)	(0.426)
Controls	Y	Y	Y
Province-Track-Year FE	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y
Observations	917,991	917,991	917,991
R-squared	0.968	0.968	0.968

Notes: This table reports the results of the main regression with export controls as the alternative measure of U.S.-China technology rivalry. The dependent variable is standardized admission scores at the college-province-track-major-year level. The main independent variable is the intensity of U.S. export controls imposed on Chinese firms at the province-major-year level. The sample covers the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-major level. We control for province-track-year, major category-province-year, and college-province-batch-year fixed effects in all columns. In columns (1)-(3), the *Export Control* variables are measured by the number of firms, the total registered capital of firms, and the total number of employees of firms included on the entity list. The Tariff Exposure variable is the weighted average tariff on Chinese exports at the province-major-year level. The Chinese tariff on foreign imported products and province-college-track-major enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6 The Effect of Export Controls on Admission Scores across College Types

Admission Score	(1)	(2)	(3)	(4)
Export Control	0.036*	0.013	-0.004	-0.046**
	(0.019)	(0.020)	(0.020)	(0.022)
Tariff	2.018***	1.330***	1.978***	0.787
	(0.426)	(0.426)	(0.490)	(0.491)
Export Control× National Elite		0.229***		0.286***
		(0.036)		(0.037)
Tariff × National Elite		4.266***		4.806***
		(0.772)		(0.803)
Export Control× Local Elite			0.137***	0.181***
			(0.035)	(0.035)
Tariff × Local Elite			0.136	1.258**
			(0.636)	(0.639)
Controls	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y	Y
Observations	917,991	917,991	917,991	917,991
R-squared	0.968	0.968	0.968	0.968

Notes: This table reports estimates of the heterogeneous effects of export controls on admission scores across different college types. The dependent variable is standardized admission scores at the college-province-track-major-year level. The main independent variables are the intensity of U.S. export controls imposed on Chinese firms (only using number of firms, not assets or employees), and its interaction terms with two college-type dummies. National elite colleges refer to universities sponsored by the 211 Project, which roughly corresponds to the top 100 universities in China. Local elite colleges refer to universities in the first batch but not sponsored by the 211 Project. The sample spans the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-major level. The Tariff variable is the weighted average tariff on Chinese exports at the province-major-year level. We control for province-track-year fixed effects, major category-province-year fixed effects, and college-province-batch-year fixed effects in all columns. The province-major-year level Chinese tariff on foreign imports and province-college-track-major level enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.6 Robustness Checks

In this section, we conduct a series of robustness checks to validate our findings. First, we investigate the effects of pre-trade war industrial policies, which may confound our estimates. Second, we exclude data after the onset of the COVID-19 pandemic. Third, we consider colleges that are directly included on the U.S. export control entity list.

Pre-Trade War Industrial Policies. In the main regressions, we find that tariffs motivated Chinese students to apply to tariff-related STEM majors. This may result from government subsidies to affected industries or firm investment responses that strengthened student confidence in the future of impacted industries. However, one concern is whether the results are influenced by pre-trade war industrial policies rather than trade war-induced policy changes. We have serveral responses to this issue. First, we control for major category-province-year fixed effects to account for location-specific demand shocks for STEM majors. Second, we conduct an event study, demonstrating that there were no systematic differences in admission scores across majors with varying tariff exposures prior to the trade war. To further address this concern, in this section, we focus on the most important pre-trade war industrial policy in China: "Made in China 2025" (MIC 2025), which supported strategic areas such as advanced manufacturing and high-end equipment manufacturing, aiming to foster innovation and technological development. We claim that this policy would not contaminate our results for two reasons. First, the MIC 2025 policy was implemented in 2015, three years before the trade war. Meanwhile, our main data spans only from 2017 to 2020. In Figure A1, we show an acceleration of government subsidies to high-tech industries only after 2017 when the U.S. started its 301 investigation. Second, MIC 2025 was implemented in 30 pilot cities after 2015 (Park, Mane, and Shen, 2024), and we repeat our main analysis excluding colleges in these pilot cities. The list of pilot cities is provided in Appendix Table A4. The regression results without these pilot cities are shown in column (1) of Table 7, and the coefficient of the core explanatory variable does not change significantly.

Excluding the Impact of the Pandemic. At the end of 2019, the COVID-19 outbreak in Wuhan, China, rapidly spread across the country, prompting the Chinese government to implement strict prevention and control measures. The pandemic inevitably had a profound impact on students, not only disrupting their studies and daily routines but also imposing immense psychological pressure and possibly influencing major choice in a number of ways. To account for this, we exclude the year 2020 from our data. The results in column (2) of Table 7 indicate that our findings remain robust.

Colleges on the U.S. Export Control Entity List. The export control entity list announced by the U.S. government includes not only firms but also 19 colleges and universities. An important question is whether our results are fully driven by these colleges. To address this, we re-estimate the main regressions after excluding these colleges from the sample. Column (3) in Table 7 demonstrates that the positive impact of tariff exposure persists for colleges not included on the entity list. In Column (4), we further investigate the effect by introducing an interaction term between tariff exposure and a dummy variable indicating whether a college is listed. For colleges included on the entity list, the effect of the tariff is significantly larger.

In Appendix B, we explore eight additional robustness exercises. First, we exclude sample from special groups of students, such as arts and sports talent programs, which follow different admission rules that rely less on NCEE scores. Second, we exclude special majors, such as teacher training programs, which require students to work in specific occupations after graduation. Third, we use alternative measures for the dependent variables including the log of original score without standardized and score percentile. Fourth, we change the core explanatory variable to U.S. tariff exposure only, excluding other countries. Fifth, we recalculate tariff exposure by only considering national level (but not province level) export shares. Sixth, we account for the upgrading or renaming of colleges to address the concern of mapping error. Seventh, we add a control variable for tariff exposure at the university's location. Eighth, we examine the potential confounding effects of enrollment quota changes. Generally, we find that our results are robust.

Table 7 Robustness checks

VARIABLES	(1) Pre-Trade War Industry Policy	(2) Excluding the Impact of the Pandemic	(3) Excluding Colleges in Entity List	(4) Interaction of Entity List Colleges
Tariff	2.225***	2.499***	1.981***	1.947***
	(0.473)	(0.465)	(0.426)	(0.422)
Tariff × Entity List College				3.577***
				(1.346)
Controls	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y	Y
Observations	633,951	638,879	897,122	918,010
R-squared	0.965	0.970	0.967	0.968

Notes: This table reports the results of several robustness checks. The dependent variable is standardized admission scores at the college-province-track-major-year level. The independent variable is the weighted average tariff imposed by all buyers of Chinese exports at the province-major-year level. The sample covers the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-major level. We control for province-track-year fixed effects, major category-province-year fixed effects, and college-province-batch-year fixed effects in all columns. Column (1) excludes colleges located in the 30 pilot cities of the MIC 2025 initiative. Column (2) excludes data from the year 2020 to eliminate the potential impact of the COVID-19 pandemic. Column (3) excludes colleges on the U.S. entity list. Column (4) includes the interaction term between tariff exposure and the dummy variable indicating whether the college is on the U.S. entity list. The province-major-year level Chinese tariff on foreign imports and province-college-track-major enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Mechanism

In the previous analysis, we show that the trade war tariffs surprisingly increased the admission scores of affected majors in elite universities. Despite the trade war, students apparently remain confident about the future of high-tech industries in China. We attribute this to two main factors: government support for affected industries and rising private demand for high-end talent. The combination of government support and firm demand for tech talent has possibly bolstered student confidence in the future of affected industries, making students more likely to pursue careers in these fields. Next, we verify these mechanisms by analyzing government subsidy behavior and firm recruitment strategies.

6.1 Trade War and Government Subsidies

A key measure of government industrial policy support for relevant industries is financial subsidies. To assess whether the government increased its support for these industries, we analyze data on subsidies provided to publicly listed companies. The dataset includes 2,641 listed manufacturing companies in China from 2017 to 2020. To evaluate the impact of tariffs on the government subsidies received by target industries, we employ the following empirical model:

$$Sub_{it} = \alpha + \beta_1 Tariff_{jt} + \beta_2 CHN\_Tariff_{jt} + X_{it} + \delta_i + \lambda_t + \epsilon_{it} \tag{10}$$

$$Tariff_{kt} = \sum_{c} \frac{Exp_{ck,2017}}{Exp_{k,2017}} \times Tariff_{ckt} \tag{11}$$

$$Tariff_{jt} = \sum_{\mathrm{k}\in \mathrm{j}} \frac{Exp_{k,2017}}{Exp_{j,2017}} \times Tariff_{kt} \tag{12}$$

Sub_{it} represents the logarithm of government subsidies received by listed company i in year t. $Tariff_{jt}$ measures the weighted average tariff across all trade partners c on Chinese industry j during the trade war. Following Brandt et al. (2017), we convert HS6-product level tariffs (k) to China's 2-digit industry level (j), weighted by the export product share of industry j in 2017 across all countries. We also account for weighted average Chinese tariffs imposed on foreign imports during the trade war. The vector X_{it} represent a set of time-varying firm-level indicators, including total assets, operating revenue, number of employees, firm age and net profit, all in logarithmic form. Additionally, we incorporate financial ratios to capture the firm's operational performance, including the current ratio, leverage ratio, and return on assets. Year and firm fixed effects are also included.

Table 8 presents the results. Column (2) includes firm-level controls, while column (3) introduces industry-year-specific trends to account for linear trends in industry expansion or contraction over time. Column (4) excludes firms that were newly listed after 2018, addressing concerns that the observed increase in subsidies could have been driven by new entrants rather than existing companies. The analysis indicates the trade war tariff surge led to an increase in government subsidies to listed companies in affected industries. Specifically, for each 1 percentage point increase of average tariff exposure, government subsidies to listed companies in that industry rose by an average of 7.99%. This suggests that the post-trade war increase in fiscal support was primarily targeted at companies impacted by the tariffs.

Table 8 Tariffs and Government Subsidies

	All sample			No Start-ups
Log(Subsidy)	(1)	(2)	(3)	(3)
Tariff	2.311	4.026*	7.992*	9.279**
	(2.100)	(2.210)	(4.164)	(4.191)
Firm Controls	N	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry#year	N	N	Y	Y
Observations	6,582	6,582	6,582	6,103
R-squared	0.815	0.831	0.833	0.836

Notes: The dependent variable is firm-year government subsidies received by listed companies in 2018-2020. The independent variable is the CIC 2-digit industry-year level average tariff exposure from 2017 and 2019 with a one period lag. The industry-level tariffs are the weighted average of HS6 product-level tariffs across all buyers of Chinese exports, with industry-specific export shares as the weights. Industry-year level Chinese tariffs on imports are included as a control variable, which are the weighted average of Chinese HS6-level import tariffs on foreign products based the import share of each industry. ST (Special Treatment) firms and firms with revenues less than or equal to zero are excluded. Column (1) contains all listed companies and includes year fixed effects and firm fixed effects. Column (2) further adds firm-level control variables including the logs of firm revenue, assets, age, number of employees, and net income, as well as the firm's liquidity ratio, leverage ratio, and asset profitability ratio. Column (3) introduces a linear time trend for each CIC 2-digit industry. Column (4) drops companies listed after 2017. each year. Standard errors are clustered at the firm level. *** p < 0.01, ** p < 0.05, * p < 0.1.

6.2 Trade War and Labor Demand

Changes in labor market demand are closely tied to college students' expectations for future employment. For instance, do companies in industries impacted by the U.S.-China trade war, such as Huawei, increase their demand for high-end talent to drive compensatory innovation? To explore this mechanism, we use monthly data on online job postings from 343 Chinese cities between 2017 and 2020, covering 220 manufacturing-related occupations. This dataset allows us to empirically analyze how tariffs affect labor demand and average wages across various occupations.

The trade war impacted occupations differently, with those in industries facing higher tariffs experiencing greater effects. Using monthly tariff data at the HS6-product-country level and the base-period export share of Chinese cities to different buyers within spectific HS6-product, we calculate monthly average tariffs at the city-HS6-product level. We then aggregate these tariffs to the city-industry level with industry-specific export shares of products as the weights. Finally, we use employment distribution data from the 2017 ACS, which details the allocation of specific occupations across industries, to calculate the city-occupation level tariff. The calculation process is shown in Appendix C.

Table A5 in the Appendix lists the most and least affected occupations. Unsurprisingly, the occupations most affected by the trade war are closely tied to high-tech and manufacturing industries. To estimate the effect of tariffs on labor demand for various occupations in China, we run the following regressions:

$$Y_{pit} = \alpha + \beta_1 Tariff_{pi,t-3} + \beta_2 CHN\_tariff_{pi,t-3} + \varphi_{pt} + \delta_{it} + \lambda_{pi} + \epsilon_{pit} \tag{13}$$

p, j, k, i, t denote the Chinese city, industry, HS6 product, occupation, and year, respectively. Y_{pit} denotes the number of job postings and the average wage for occupation i in city p during period t. $Tariff_{pi,t-3}$ and $CHN\_Tariff_{pi,t-3}$ capture the weighted average tariff on Chinese exports and imports for occupation i in city p, respectively, lagged by three months to account for labor market adjustment. The subscript t indicates the year-month. We check the robustness of our results by varying the lag periods, as detailed in Appendix D.

Table 9 presents the impact of the trade war on labor demand. The dependent variables in columns (1) and (2) are the number of job postings and average wages, respectively. Overall, we find that tariffs affecting specific occupations reduced average wages. In columns (3) and (4), we classify occupations into R&D-related and non-R&D-related categories based on O*NET classifications, with two main findings. First, job demand for R&D-related occupations increased significantly. This finding partially explains why only students from elite universities showed a notable increase in their intention to enroll in STEM majors. Second, job postings and average wages for R&D-related occupations increased significantly compared to non-R&D occupations. A 1 percentage point increase in the weighted average tariff correlates with a 13.67% increase in job demand and 2.77% increase in wage for R&D occupation compared to non-R&D Occupation.

Table 9 Effects of Tariffs on Job Postings and Wages

	(1) Log(Postings)	(2) Log(Wage)	(3) Log(Postings)	(4) Log(Wage)
Tariff	-2.505	-3.790***	-5.414	-4.291***
	(3.418)	(0.870)	(4.057)	(1.036)
Tariff $\times$ R&D			13.661***	2.772**
			(4.847)	(1.293)
Controls	Y	Y	Y	Y
City-Year-Month FE	Y	Y	Y	Y
Occupation-Year-Month FE	Y	Y	Y	Y
City-Occupation FE	Y	Y	Y	Y
Observations	789,074	718,086	789,074	718,086
R-squared	0.998	0.921	0.998	0.921

Notes: This table reports estimates of the effect of tariffs on job postings and wages. The dependent variable is the city-occupation level number of job postings (columns 1 and 3) and average wages (columns 2 and 4) from major online job posting platforms. The main independent variable is city-occupation level average tariff exposure with a 3-month lag. The sample period spans from January 2017 to December 2020. Columns (3) and (4) include the interaction of tariff exposure with an R&D dummy variable. The R&D dummy equals 1 if the occupation is classified under the "Research, Development, Design, and Practitioners; Technologists and Technicians" category within the STEM occupation list on the O*NET website, and 0 otherwise. All regressions include city-year-month fixed effects, occupation-year-month fixed effects, and city-occupation fixed effects. The Chinese tariff on foreign imported products and its interactions with the R&D dummy are included as control variables in all columns. Standard errors are clustered at the city-month level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.3 Trade War and Public Awareness

Our results thus far indicate a robust and positive relationship between tariff exposure and the admissions scores of college majors. However, we lack direct evidence of public awareness regarding the U.S.-China trade war, which is a crucial prerequisite for the trade war to influence students' major choices. To address this issue, we analyze search activity on Baidu, China's leading search engine, as supplementary evidence of public awareness about the U.S.-China trade war. The Baidu Index, comparable to Google Trends, provides a scaled measure of search intensity for specific keywords and can be analyzed by region and time.

We focus on two keywords: "U.S.-China trade war (*zhongmei maoyi zhan*)" and "U.S.-China trade friction (*zhongmei maoyi moca*)". Using the Baidu Index, we calculate search intensity at the city-month level for these keywords to gauge public attention to U.S.-China trade tensions across different regions. To quantify city-level tariff exposure, we combine monthly product tariff data across trade partners from 2017 to 2019 using the 2017 export product share of Chinese cities, constructing a city-year-month level indicator of tariff exposure. We then estimate the following model:

$$Baidu\ Index_{i,t} = \alpha + \beta_1 Tariff_{i,t} + \beta_2 CHN\_Tariff_{i,t} + X_{i,t} + \delta_i + \lambda_t + \epsilon_{i,t} \tag{14}$$

$$Tariff_{ik,t} = \sum_{c} \frac{Export_{ick,2016}}{Export_{ik,2016}} \times Tariff_{ck,t} \tag{15}$$

$$Tariff_{i,t} = \sum_{k} \frac{Export_{ik,2016}}{Export_{i,2016}} \times Tariff_{ik,t} \tag{16}$$

Here, i represents the city, t denotes the specific month (e.g., March 2018), c represents the trade partner countries and k refers to the HS6 product. The Baidu Index for city i in month t is expressed in logarithmic form. $Tariff_{i,t}$ represents the weighted average of foreign tariffs on exports of city i in month t. We include $CHN\_Tariff_{i,t}$ as a control variable. The vector $X_{i,t}$ captures time-varying city characteristics, such as population size, mobile phone penetration, and internet penetration. We also include city fixed effects δ_i

and year-month fixed effects λ_t as controls.

Table 10 demonstrates that the tariff surge during the U.S.-China trade war led to a significant increase in public search intensity. We analyze the monthly Baidu Index from two types of terminals: mobile terminals (columns 1–3) and personal computer (PC) terminals (columns 4–6). As tariff exposure increased, search intensity for the keyword "U.S.-China trade war (*zhongmei maoyi zhan*)" rose significantly on both terminals, while the keyword "China-U.S. trade friction (*zhongmei maoyi moca*)" showed a significant increase on PC terminals. This suggests that higher tariffs imposed on a city were associated with greater local public awareness of the trade war. In columns (3) and (6), the dependent variable is the combined Baidu Index for the two keywords, and the results remain consistent.

Table 10 Tariffs and Public Awareness of the Trade War

	Mobile Terminal			PC Terminal		
	(1) U.S.-China Trade war	(2) U.S.-China Trade friction	(3) Composite Index	(4) U.S.-China Trade war	(5) U.S.-China Trade friction	(6) Composite Index
Tariff	5.457***	4.646	3.195**	3.340**	8.618**	5.468***
	(3.387)	(1.078)	(2.267)	(2.227)	(2.369)	(3.340)
City Controls	Y	Y	Y	Y	Y	Y
Year-Month FE	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Observations	5,434	5,434	5,434	5,434	5,434	5,434
R-squared	0.892	0.715	0.895	0.885	0.673	0.896

Notes: This table shows the effect of city tariff exposure on public internet searches concerning the trade war. The dependent variable is the city-level Baidu Index, which is the logarithm of the number of searches for specific keywords on Baidu.com using either mobile (columns 1-3) or PC terminals (column 4-6). The independent variable is city-level average tariff exposure. The composite index for the trade war is constructed by aggregating the Baidu Index for the two trade-war-related keywords including "U.S.-China trade war (*zhongmei maoyi zhan*)" and "U.S.-China trade friction (*zhongmei maoyi moca*)". The city-level average Chinese tariff on foreign imports is included as a control variable in all columns. All regressions include year-month fixed effects and city fixed effects. City-level controls include the population, the penetration rate of mobile phone usage, and the internet penetration rate. Standard errors are clustered at the city-month level. *** p < 0.01, ** p < 0.05, * p < 0.1.

7 Conclusion

In this paper, we investigate the impact of the U.S.-China trade war on the college major choices of Chinese students. Surprisingly, we find that the U.S. punitive tariffs did not succeed in curbing the flow of talent into high-tech majors in China. On the contrary, we observe an increase in HSEE cutoff scores for these majors, particularly for STEM majors at national elite universities. This outcome is driven by the Chinese government's response, which involved increasing subsidies for firms and industries affected by the tariffs, and firms' increased investment in R&D. China's strategy of defensive innovation attracted more students to pursue careers in high-tech industries.

Our results suggest that the consequences of anti-free trade policies can be complicated and may deviate from policymakers' expectations, especially if they overlook the reactions of their trading partners. A punitive tariff aimed at restricting the high-tech development of potential competitors may inadvertently lead to increased innovation investment by the targeted nation. Superficial protectionism can ultimately harm both countries.

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Appendix

A Additional Tables and Figures

Table A1 Additional Summary Statistics

Variable	Mean	Sd	Min	Max	N
Tariff	0.007	0.006	0	0.050	934477
Chinese Tariff	0.007	0.006	0	0.054	934477
Standardized Admission Score	0	0.998	-6.056	4.984	934477
No. of Admission	7.907	21.991	1	1297	934477

Notes: The tariffs are constructed as weighted average product tariffs across all Chinese trade partners, including but not limited to the U.S. (Equation 1). Standardized admission scores are province-college-track-major-year level, constructed by standardizing the raw admission scores at the province-track-year level.

Table A2 Industry Distribution

College major	Top three destinations: current industry	Employment shares
Agriculture	Agriculture, Forestry, Fishing, and Hunting	17.43%
	Educational Services	12.06%
	Professional, Scientific, and Technical Services	10.96%
Environment and Natural Resources	Public Administration	16.40%
	Professional, Scientific, and Technical Services	15.64%
	Educational Services	12.73%
Architecture	Professional, Scientific, and Technical Services	45.67%
	Construction	8.12%
	Educational Services	7.45%
Area, Ethnic, and Civilization Studies	Educational Services	24.19%
	Professional, Scientific, and Technical Services	15.02%
	Health Care and Social Assistance	12.74%
Communications	Professional, Scientific, and Technical Services	15.52%
	Educational Services	14.36%
	Information	10.95%
Communication Technologies	Professional, Scientific, and Technical Services	19.64%
	Information	15.46%
	Manufacturing	10.45%
Computer and Information Sciences	Professional, Scientific, and Technical Services	31.61%
	Finance and Insurance	10.01%
	Manufacturing	9.93%
Cosmetology Services and Culinary Arts	Accommodation and Food Services	35.09%
	Other Services, Except Public Administration	14.81%
	Retail Trade	7.60%
Education Administration and Teaching	Educational Services	59.46%
	Health Care and Social Assistance	8.99%
	Retail Trade	4.19%
Engineering	Manufacturing	25.48%
	Professional, Scientific, and Technical Services	24.91%
	Educational Services	7.01%

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Table A2 – continued from previous page

College major	Top three destinations: current industry	Employment shares
Engineering Technologies	Manufacturing	25.48%
	Professional, Scientific, and Technical Services	18.17%
	Educational Services	6.63%
Linguistics and Foreign Languages	Educational Service	31.59%
	Professional, Scientific, and Technical Services	12.72%
	Health Care and Social Assistance	11.56%
Family and Consumer Sciences	Educational Services	28.49%
	Health Care and Social Assistance	24.98%
	Retail Trade	6.90%
Law	Professional, Scientific, and Technical Services	30.41%
	Public Administration	15.30%
	Educational Services	8.21%
English Language, Literature, and Composition	Educational Services	27.54%
	Professional, Scientific, and Technical Services	14.39%
	Health Care and Social Assistance	9.63%
Liberal Arts and Humanities	Educational Services	23.70%
	Health Care and Social Assistance	12.07%
	Professional, Scientific, and Technical Services	10.57%
Library Science	Educational Services	32.35%
	Information	23.20%
	Health Care and Social Assistance	8.50%
Biology and Life Sciences	Health Care and Social Assistance	36.17%
	Educational Services	16.68%
	Professional, Scientific, and Technical Services	11.94%
Mathematics and Statistics	Educational Services	27.07%
	Professional, Scientific, and Technical Services	18.47%
	Finance and Insurance	10.81%
Military Technologies	Public Administration	32.65%
	Professional, Scientific, and Technical Services	14.29%
	Retail Trade	8.16%
Interdisciplinary and Multi-Disciplinary Studies (General)	Health Care and Social Assistance	22.11%
	Educational Services	20.60%
	Professional, Scientific, and Technical Services	11.17%
Physical Fitness, Parks, Recreation, and Leisure	Health Care and Social Assistance	24.10%
	Educational Services	19.39%
	Arts, Entertainment, and Recreation	9.99%
Philosophy and Religious Studies	Educational Services	19.79%
	Other Services, Except Public Administration	16.74%
	Professional, Scientific, and Technical Services	15.15%
Theology and Religious Vocations	Other Services, Except Public Administration	35.45%
	Educational Services	14.33%
	Health Care and Social Assistance	9.81%
Physical Sciences	Health Care and Social Assistance	18.21%
	Educational Services	17.19%
	Professional, Scientific, and Technical Services	17.14%
Nuclear, Industrial Radiology, and Biological Technologies	Health Care and Social Assistance	55.13%
	Professional, Scientific, and Technical Services	8.97%
	Educational Services	6.41%
Psychology	Health Care and Social Assistance	28.19%
	Educational Services	20.92%
	Professional, Scientific, and Technical Services	9.69%
Criminal Justice and Fire Protection	Public Administration	35.94%
	Health Care and Social Assistance	9.57%
	Educational Services	8.55%
Public Affairs, Policy, and Social Work	Health Care and Social Assistance	38.65%
	Educational Services	16.25%
	Public Administration	12.40%
Social Sciences	Professional, Scientific, and Technical Services	18.38%
	Educational Services	14.65%
	Public Administration	11.04%
Construction Services	Construction	53.23%
	Professional, Scientific, and Technical Services	8.75%
	Manufacturing	5.31%
Electrical and Mechanic Repairs and Technologies	Manufacturing	27.10%
	Transportation and Warehousing	9.81%
	Other Services, Except Public Administration	8.41%
Transportation Sciences and Technologies	Transportation and Warehousing	34.91%

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Table A2 – continued from previous page

College major	Top three destinations: current industry	Employment shares
	Public Administration	14.06%
	Manufacturing	10.11%
Fine Arts	Educational Services	19.47%
	Professional, Scientific, and Technical Services	15.95%
	Retail Trade	9.86%
Medical and Health Sciences and Services	Health Care and Social Assistance	63.52%
	Educational Services	10.41%
	Retail Trade	5.44%
Business	Professional, Scientific, and Technical Services	15.13%
	Finance and Insurance	13.61%
	Manufacturing	9.82%
History	Educational Services	23.42%
	Professional, Scientific, and Technical Services	16.02%
	Public Administration	9.07%

Notes: This table shows the top 3 employment industries of workers with specific college majors. The employment share is equal to the number of employees in a given industry with a specific college major divided by the total number of employees with that degree, calculated based on the survey data from ACS in 2017.
Source: Employment data from the ACS.

Table A3 Majors with the Largest Tariff Exposure and Score Increases in Figure 3

Major Group	Observations	Share	Mean Δ Tariff
Mechanical	4,801	47.92	0.0162616
Materials	1,493	14.9	0.0142444
Electronic Information	743	7.42	0.0146618
Instrumentation	526	5.25	0.0158274
Aerospace	389	3.88	0.0225628
Food Science and Engineering	236	2.36	0.0159818
Textile	233	2.33	0.0148243
Logistics Management and Engineering	198	1.98	0.0146641
Automation	198	1.98	0.0132477
Electricity	179	1.79	0.0153592
Chemical and Pharmaceutical	175	1.75	0.0123619
E-commerce	126	1.26	0.0148068
Plant Production	113	1.13	0.0132249
Industrial Engineering	102	1.02	0.0142453
Light Industry	102	1.02	0.014758
Agricultural Engineering	81	0.81	0.0172874
Safety Science and Engineering	70	0.7	0.013777
Transportation	59	0.59	0.0137731
Management Science and Engineering	59	0.59	0.013777
Forestry Engineering	39	0.39	0.0150369
Mechanics	31	0.31	0.014515
Nature Conservation and Environmental Ecology	17	0.17	0.0144559
Geology	16	0.16	0.0126409
Herbology	15	0.15	0.0125426
Surveying and Mapping	10	0.1	0.0126409
Environmental Science and Engineering	8	0.08	0.0165414

Notes: This table shows the major groups which experienced the largest increases in tariff exposure during the U.S. - China trade war, included in the bins on the far right of Figure 3. The observations are the number of province-track-college-major enrollment admissions under this major group. The share calculates the proportion of this specific major group in total admissions.

Table A4 The Pilot Cities of MIC2025

Province	City
Zhejiang	Ningbo, Huzhou
Liaoning	Shenyang
Jilin	Changchun
Jiangsu	Nanjing, Wuxi, Changzhou, Zhenjiang, Suzhou
Guangdong	Foshan, Zhaoqing, Jiangmen, Zhuhai, Yangjiang, Zhongshan, Guangzhou
Fujian	Quanzhou
Henan	Zhengzhou, Luoyang, Xinxiang
Hunan	Zhuzhou, Xiangtan, Hengyang, Changsha
Sichuan	Chengdu
Anhui	Hefei
Hubei	Wuhan
Jiangxi	Ganzhou
Shandong	Qingdao
Ningxia	Wuzhong

Table A5 The Most and Least Affected Occupations

List A: The Most Affected Occupations

No.	Occupation Type	Tariff Exposure
1	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	0.2426104
2	Aerospace Engineers	0.1439608
3	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	0.1418607
4	Machinists	0.1330027
5	Tool and Die Makers	0.1273870
6	Mechanical Engineers	0.1127389
7	Tire Builders	0.1077753
8	Structural Metal Fabricators and Fitters	0.1046330
9	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	0.1035964
10	Materials Engineers	0.1030720
11	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	0.1003655
12	Engine and Other Machine Assemblers	0.0998258
13	Sawing Machine Setters, Operators, and Tenders, Wood	0.0988292
14	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	0.0929729
15	Sewing Machine Operators	0.0910460
16	Molders, Shapers, and Casters, Except Metal and Plastic	0.0862859
17	Rolling Machine Setters, Operators, and Tenders, metal and Plastic	0.0856744
18	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	0.0819059
19	Paper Goods Machine Setters, Operators, and Tenders	0.0767539
20	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	0.0762461

List B: The Least Affected Occupations

No.	Occupation Type	Tariff Exposure
1	Childcare Workers	0.0000086
2	Meeting and Convention Planners	0.0000240
3	Social and Community Service Managers	0.0000388
4	Insurance Sales Agents	0.0000658
5	Food Service and Lodging Managers	0.0000669
6	Nonfarm Animal Caretakers	0.0000775
7	Respiratory Therapists	0.0001104
8	Physical Therapists	0.0001158
9	First-Line Supervisors of Fire Fighting and Prevention Workers	0.0001213
10	Residential Advisors	0.0001494
11	Insurance Underwriters	0.0001641
12	Maids and Housekeeping Cleaners	0.0001655
13	Insurance Claims and Policy Processing Clerks	0.0001697
14	Court, Municipal, and License Clerks	0.0001776
15	Registered Nurses	0.0001820
16	Retail Salespersons	0.0001893
17	Pharmacists	0.0001926
18	Waiters and Waitresses	0.0002090
19	Actors, Producers, and Directors	0.0002166
20	Library Technicians	0.0002263

Notes: This table shows the top 20 occupations that most and least affected by tariff in 2019. We first calculate the province-occupation level tariff exposure by equation 19, and then take average of province-occupation level tariff to get the tariff exposure of each occupation.

Source: The tariff data from the Customs General Administration of China, the United States Census Bureau, the United States Trade Representative (USTR), the WITS tariff dataset, and the United States International Trade Commission (USITC); the employment data from the ACS survey data.

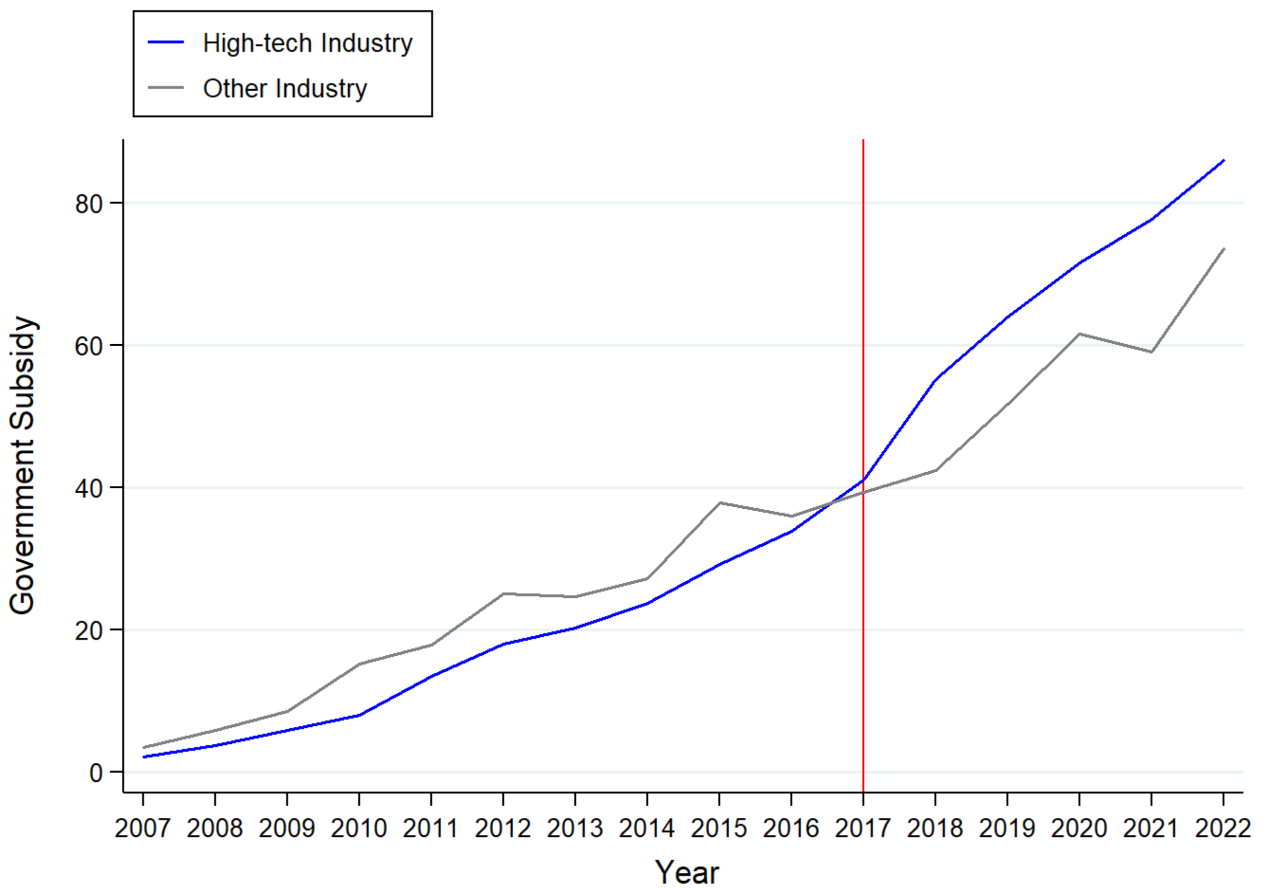

Figure A1 Government Subsidies to Manufacturing

Notes: This figure shows the changes over time in total government subsidies received by listed manufacturing companies in high-tech industries and other industries. The data spans 2007 to 2022. The vertical axis represents the total value of government subsidies received by listed companies by industry group, measured in billion yuan. We exclude companies under Special Treatment (ST) designation. The high-tech industries include Special Equipment Manufacturing, Instrument Manufacturing, Pharmaceutical Manufacturing, Transport Equipment Manufacturing, and Automobile Manufacturing.

Source: The annual reports of listed companies.

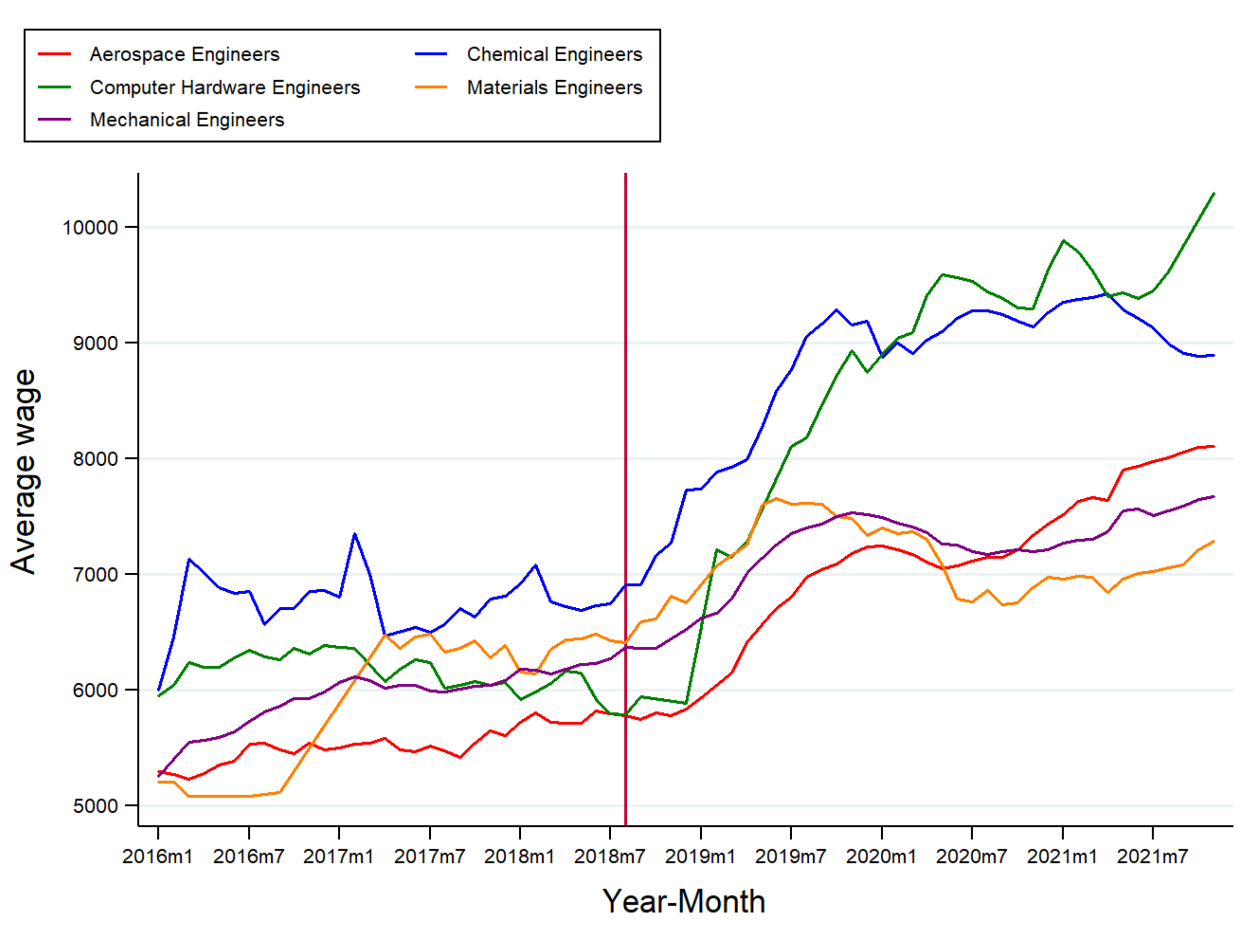

Figure A2 Average Wages for Engineering Occupations

Notes: This figure shows the monthly wage fluctuations for engineer positions. The data spans 2016:1 to 2021:11. The vertical axis represents the average wage of such positions, measured in yuan. The observation window for calculating the average wage of positions spans 6 months before and after the reference period.

Source: The job postings and wage data were collected and processed by the authors through web scraping techniques.

B Robustness Checks

B.1 Excluding Special Groups of Students

We consider three types of special student groups: ethnic minority students, students with predetermined employment, and students in dedicated arts or sports talent programs. First, minority candidates often have different admission standards. We exclude provinces with minority populations exceeding 30%. Based on China's national census data in 2020, we exclude Xinjiang, Tibet, Yunnan, Guizhou, Ningxia, and Qinghai. The results in column (1) of Table B1 show minimal change in the regression coefficient after excluding these regions. Column (2) presents a separate regression for provinces with high minority populations, showing a similar statistically significant impact of tariff exposure on students from these areas. Second, candidates with predetermined employment are those recruited for specific industries or enterprises with known post-graduation positions and fixed service years. These candidates do not need to consider the employment prospects of their majors. We exclude these candidates, and the results, shown in column (3), remain robust. Third, we exclude students admitted through special talent exams in sports or arts, as their admission processes differ from the regular college entrance exam. The results in column (4) show that the core conclusions remain unchanged.

B.2 Excluding Special Majors

We consider three types of special majors: teacher training majors, China-foreign cooperative majors, and majors newly established by the Chinese Ministry of Education after 2017. First, students in teacher training majors need to master both subject knowledge and pedagogical skills, with most graduates working in primary and secondary education. These majors are barely affected by U.S.-China trade friction. In column (1) of Table B2, we exclude teacher training majors and found the core conclusions were unaffected. A separate regression in column (2) confirms that tariffs also had smaller positive impacts on these majors, without statistical significance. Second, China-foreign cooperative majors, jointly offered by Chinese and foreign universities, often provide opportunities for students to study abroad. Students apply for these majors mainly to access labor markets in other countries. In column (3), we exclude these majors, and the results remain robust. Finally, we exclude majors newly established by the Ministry of Education after 2017, such as AI and digital economics in column (4), and the key coefficient does not change significantly.

Table B1 Excluding Special Student Group

Admission Score	(1) Non-Minority	(2) Minority Province	(3) Drop Oriented Student	(4) Drop Arts/sports Student
Tariff	2.049***	3.197**	2.118***	2.143***
	(0.448)	(1.380)	(0.427)	(0.428)
Controls	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y	Y
Observations	806,281	111,729	917,858	917,292
R-squared	0.969	0.966	0.968	0.968

Notes: This table reports the results of the robustness checks excluding special student groups from the regression. The dependent variable is standardized admission scores at the college-province-track-major-year level. The main independent variable is the weighted average tariff on Chinese exports at the province-major-year level. In column (1), we exclude minority provinces, defined as provinces where the minority population exceeds 30%: Xinjiang, Tibet, Yunnan, Guizhou, Ningxia, and Qinghai. In column (2), we include only minority provinces. In column (3), we exclude students admitted through specific occupational programs with job placement requirements and fixed service years. In column (4), we exclude students admitted through special sports or arts admission channels. We control for province-track-year fixed effects, major category-province-year fixed effects, and college-province-batch-year fixed effects in all columns. The province-major-year level average Chinese tariff on foreign imports and province-college-track-major level enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.3 Alternative Measures of the Dependent Variable

In the baseline regression, we use standardized admission scores as the dependent variable. To ensure the robustness of the results, we also consider two alternative measures. The first is the absolute level of scores, represented by the log of the original admission score. The second is the ranking based on admission scores within the province and track, consistent with the measurement used by Li et al. (2024). The results in columns (2) and (3) of Table B3 indicate that our findings remain robust. According to column (3), a 1 percentage point increase in tariff exposure for a major results in an average improvement of 0.28 percentage points in score percentile, which equals 393 positions higher in the average province-track admission ranking.[14]

[14] There were on average 140,329 NCEE takers per province-track each year from 2017 to 2020. Therefore, an increase of 0.28 percentage points in score percentile ranking means an improvement of 140,329 $\times$ 0.28% = 392.92 positions. Due to the large variation in the number of applicants across different provinces in China, the impact will be larger in specific provinces. For example, in Henan Province, the average number of applicants for the science track was 426,850, so a one percentage point increase in major tariff exposure would result in an improvement of 426,850 $\times$ 0.28% = 1,195.18 positions in the admissions ranking.

Table B2 Excluding Special Major Groups

Admission Score	(1) Non-teacher Major	(2) Teacher Major	(3) Drop China-foreign Program	(4) Drop New Majors
Tariff	2.045***	1.725	2.354***	2.084***
	(0.426)	(1.951)	(0.383)	(0.431)
Controls	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y	Y
Observations	874,409	40,076	903,712	915,882
R-squared	0.970	0.970	0.972	0.968

Notes: This table reports the results of the robustness checks excluding special major groups from the regression. The dependent variable is standardized admission scores at the college-province-track-major-year level. The main independent variable is the weighted average tariff on Chinese exports at the province-major-year level. In column (1), we exclude teacher training programs. In column (2), we include only teacher training programs. In column (3), we exclude China-foreign cooperative majors between Chinese and foreign universities, which enable students to study abroad as part of their degree. In column (4), we exclude new majors introduced by the Ministry of Education after 2017. We control for province-track-year fixed effects, major category-province-year fixed effects, and college-province-batch-year fixed effects in all columns. The province-major-year level Chinese tariff on foreign imports and province-college-track-major level enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.4 Using Only U.S. Punitive and Chinese Retaliatory Tariffs

In baseline results, we construct the tariff shock during the U.S.-China trade war by considering both the U.S. punitive tariffs and tariffs imposed by other countries on Chinese products. To further verify whether the U.S. punitive tariffs are the driving force of defensive innovation, we conduct a robustness check by excluding the import tariffs imposed by other countries and use only U.S. punitive tariff exposure as the core explanatory variable. Simultaneously, we replace the import tariffs with only China's retaliatory tariffs against the U.S. as a control. The regression results, shown in Table B4, indicate that the U.S. punitive tariffs significantly raised the admission scores for affected majors, consistent with our previous findings.

B.5 Using Only National Export share in Constructing Tariff Exposure

In the baseline results, we construct tariff exposure using province-level export share across products and trade partner. The underlying assumption we make is that students from different provinces experience different tariff shocks when choosing majors. For a

Table B3 Alternative Measures of the Dependent Variable

	(1) Standardized Admission Score	(2) Ln(Admission score)	(3) Score Percentile
Tariff	2.134***	0.208***	0.280*
	(0.428)	(0.050)	(0.140)
Controls	Y	Y	Y
Province-Track-Year FE	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y
Observations	918,010	918,010	918,010
R-squared	0.968	0.979	0.949

Notes: This table reports the results of the main regression with alternative measures of admission scores. In column (1), the dependent variable is the standardized admission score, as in the main regression, and serves as the baseline result for reference. The dependent variables in columns (2) and (3) are the log of the original admission scores and the score percentile, respectively. The score percentiles are calculated within each province-year-track cluster, which is equal to the provincial admission cutoff rankings of the NCEE, divided by the total number of exam-takers. All dependent variables are measured at the college-province-track-major-year level. The independent variable is the weighted average tariff on Chinese exports at the province-major-year level. The sample covers the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-major level. We control for province-track-year fixed effects, major category-province-year fixed effects, and college-province-batch-year fixed effects in all columns. The province-major-year level Chinese tariff on foreign imports and province-college-track-major enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

specific major m, the variation in tariff exposure stems from: (1) differences in initial export (product-country) composition at the province level; and (2) differences in the tariffs on Chinese exports over time at the product level. This setting corresponds to reality in two key respects. First, there are informational frictions and students mainly get information from surrounding social networks within their provinces. Second, students are more concerned about local labor markets in their location province, as many of them will go back to work in their hometown after graduation.

One concern is that if information and migration are very mobile across provinces, our results may capture the effect on the admission score due to differences in export product share across provinces, rather than tariff changes. Therefore, we calculate the tariff exposure using only China's national export share across product and trade partner, so that the tariff shocks for specific majors are the same across different provinces, removing all possibility of capturing provincial structure effects. The results in Table B5 show that the coefficient on tariffs is still significantly positive, but the magnitude is reduced compared to in Table 2.

Table B4 Using Only U.S. Punitive and Chinese Retaliatory Tariffs

	Standardized Admission Score			
	(1)	(2)	(3)	(4)
U.S. Punitive Tariff	1.930***	1.946***	1.968***	1.522***
	(0.269)	(0.257)	(0.255)	(0.162)
Controls	Y	Y	Y	Y
Year-Province-Track FE	Y	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y	Y
Province-College FE	Y	Y	N	N
Year-College FE	N	Y	N	N
Year-Province-College FE	N	N	Y	N
Year-Province-College-Batch FE	N	N	N	Y
Observations	918,010	918,010	918,010	918,010
R-squared	0.923	0.927	0.932	0.968

Notes: This table reports estimates of the effect of U.S. punitive tariffs. In this regression, we do not consider other countries in calculating tariff exposure. The dependent variable is the standardized admission scores at the college-province-track-major-year level. The independent variable is the weighted average punitive tariff imposed by the U.S. on Chinese exports at the province-major-year level. The sample covers the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-major level. We control for province-track-year fixed effects and major category-province-year fixed effects in all columns. In column (1), we further control for college-province fixed effects. In column (2), we additionally control for college-year fixed effects. In column (3), we add college-province-year fixed effects. In column (4), we further control for college-province-batch-year fixed effects. The province-major-year level Chinese retaliatory tariff on U.S. products and province-college-track-major level enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.6 College-Specific Shocks: Upgrades and Renames

There are two main college-level shocks during the trade war. First, some three-year colleges were upgraded to universities. Second, some colleges changed their names, typically changing from a college to a university or some other large shift in structure. Previous research indicates that changes in college names can significantly influence enrollment (Eble and Hu, 2022). To control for these factors, we exclude colleges that upgraded or were renamed during the trade war. Columns (3) and (4) of Table B6 show that our key conclusions remain unaffected.

Table B5 Using Only National Export Structure in Constructing Tariff Exposure

Variables	Standardized Admission Score			
	(1)	(2)	(3)	(4)
Tariff Exposure	1.858***	2.031***	2.192***	1.257***
	(0.925)	(0.845)	(0.830)	(0.565)
Controls	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y	Y
College-Province FE	Y	Y	N	N
College-Year FE	N	Y	N	N
College-Province-Year FE	N	N	Y	N
College-Province-Batch-Year FE	N	N	N	Y
Observations	918,010	918,010	918,010	918,010
R-squared	0.923	0.927	0.931	0.968

Notes: This table reports estimates of the effect of the tariff shock on admission scores. The dependent variable is standardized admission scores at the college-province-track-major-year level. The independent variable is the weighted average tariff on Chinese exports at major-year level, which does not vary across provinces. The sample covers the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-major level. We control for province-track-year fixed effects and major category-province-year fixed effects in all columns. In column (1), we further control for college-province fixed effects. In column (2), we additionally control for college-year fixed effects. In column (3), we add college-province-year fixed effects. In column (4), we further control for college-province-batch-year fixed effects. The major-year level Chinese tariffs on foreign imports and province-college-track-major level enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.7 University Location and City-level Tariffs

In our main regression, tariff exposure is calculated by students' hometown province. Students might also consider conditions in a university's city when choosing their college-major combinations. In this section, we further include tariff exposure for the city where the university is located. The results in column (5) of Table B6 indicate that the city-level tariff where the university is located has a significant positive impact on admission scores, consistent with that of tariff at the province-major level.

Table B6 Other Robustness Checks

Admission Score	(1) Drop Upgrading Colleges	(2) Drop Renamed Colleges	(3) Add City-Level Tariffs
Tariff	2.114***	2.147***	3.194***
	(0.429)	(0.430)	(0.532)
College Location Tariff			2.293*
			(1.268)
Controls	Y	Y	Y
Province-Track-Year FE	Y	Y	Y
Major Category-Province-Year FE	Y	Y	Y
College-Province-Batch FE	N	N	Y
College-Province-Batch-Year FE	Y	Y	Y
Observations	914,726	911,657	583,089
R-squared	0.968	0.968	0.965

Notes: This table reports the results of other robustness checks. The dependent variable is standardized admission scores at the college-province-track-major-year level. The independent variable is the weighted average tariff on Chinese exports at the province-major-year level. The sample covers the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-major level. We control for province-track-year fixed effects, major category-province-year fixed effects, and college-province-batch-year fixed effects in all columns. Column (1) excludes colleges that were upgraded from three-year colleges to universities. Column (2) excludes colleges that were renamed after 2017. Column (3) includes city-level tariffs for the city where the university is located. The province-major-year level Chinese tariff on foreign imports and province-college-track-major level enrollment are included as control variables in all columns. Standard errors are clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.8 Total Enrollment Shocks

Assuming that students' preferences for majors and total enrollment remain constant, a larger enrollment quota (i.e., the supply of university seats) for a specific major reduces the difficulty of entering that major, causing the corresponding admission score threshold to drop. It is possible that quotas increased for majors exposed to the U.S.-China trade war, as part of the government response to the tariffs. Therefore, changes in program enrollments could confound our identification strategy. To alleviate this concern, we already directly control for enrollment quotas in our main regression setting.

Furthermore, we replace the dependent variable with the enrollment quota for each major to examine whether the quota has increased for majors affected by the tariff. This can be seen as an additional strategy employed by the Chinese government to foster defensive innovation. Columns (1)-(3) of Table B7 use the logarithm of the enrollment quota, while columns (4)-(6) use the enrollment quota share. The enrollment quota share is calculated as the share of a major's quota for a specific college in a province over the total quota for that college in the same province.

The result in column (1) indicates that enrollment quotas for affected majors significantly increased during the trade war, suggesting that the Chinese government aimed to develop human capital in targeted fields to compete with the U.S. This finding also implies that the baseline results may underestimate the rise in student interest in STEM fields if the enrollment quota were not controlled for. If major demand remains constant and enrollment numbers expand, admission scores would be expected to decline.

Column (2) excludes majors established after 2017. Column (3) introduces interaction terms between tariffs and two types of elite college dummies to examine how new university seats were allocated across college types. The results in column (3) reveal that the increase in enrollment is primarily driven by elite colleges. Specifically, the positive effect of tariffs on enrollment is most pronounced for national elite colleges, weaker for local elite colleges, and absent for regular colleges.

A potential concern is that the rise in enrollment could be a consequence of the national college enrollment expansion policy. To address this, in columns (4)-(6), we replace the dependent variable with the share of specific major enrollments relative to total enrollment for each college in the corresponding province, which measures the allocation of enrollment across majors within a college. The conclusions remain unchanged.

Table B7 Tariff Effects on Enrollment

	Ln(Enrollment Quota)			Enrollment Quota Share		
	(1) All Majors	(2) Drop New Majors	(3) By College Type	(4) All Majors	(5) Drop New Majors	(6) By College Type
Tariff	2.866***	3.063***	-0.435	0.167***	0.176***	0.013
	(0.859)	(0.859)	(0.898)	(0.056)	(0.056)	(0.056)
Tariff × National Elite			9.659***			0.491***
			(1.667)			(0.110)
Tariff × Local Elite			4.672***			0.181***
			(1.052)			(0.060)
Controls	Y	Y	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y	Y	Y
Major Category- Province-Year FE	Y	Y	Y	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y	Y	Y	Y
Observations	944,549	942,397	942,397	944,549	942,397	942,397
R-squared	0.779	0.779	0.780	0.774	0.774	0.775

Notes: This table reports estimates of the effects of tariffs on enrollment quotas by major. The dependent variable is the logarithm of the enrollment quota for each major (Column 1-3) and the enrollment quota share for each major (Column 4-6). The enrollment quota share is defined as the ratio of a colleges' enrollment quota for a specific major in a given province to the total enrollment quota of that college in the same province. The independent variables are the weighted average tariff on Chinese exports at the province-major-year level, and its interaction term with two college type dummy variables. Columns (1) and (4) include all majors. Columns (2) and (5) drop new majors established after 2017. Columns (3) and (6) include the interaction terms between tariff exposure and college type. National elite colleges refer to universities sponsored by the 211 Project, which roughly corresponds to the top 100 universities in China. Local elite colleges refer to universities in the first admissions batch but not sponsored by the 211 Project. The sample spans 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-major level. We control for province-track-year fixed effects, major category-province-year fixed effects, and college-province-batch-year fixed effects in all columns. The province-major-year level Chinese tariff on foreign imports (and its interactions with elite university dummies) and province-college-track-major level enrollment are included as control variables in all columns. This table reports standard errors clustered at the college level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C Calculation of Tariff Exposure at the City-occupation Level

The calculation of tariff exposure at the city-occupation level is defined as follows:

$$Tariff_{pkt} = \sum_{c} \frac{Export_{pck,2016}}{Export_{pk,2016}} \times Tariff_{pckt} \tag{17}$$

$$Tariff_{pjt} = \sum_{\mathrm{k \in j}} \frac{\frac{1}{\mathrm{N_k}} Export_{pk,2016}}{Export_{pj,2016}} \times Tariff_{pkt} \tag{18}$$

$$Tariff_{pit} = \sum_{j} Weight_{ij,2017} \times Tariff_{pjt} \tag{19}$$

$$Weight_{ij,2017} = \frac{Employ_{ij,2017}}{\sum_j Employ_{ij,2017}} \tag{20}$$

$Tariff_{ckt}$ is the tariff imposed by destination country c on product k from China in year t. $\frac{Export_{pck,2016}}{Export_{pk,2016}}$ is the share of product k from city p sold to country c in 2016.[15] $\frac{\frac{1}{N_k} Export_{pk,2016}}{Export_{pj,2016}}$ calculates the share of product k in industry j, In cases where an HS-6 product is associated with multiple industries, we distribute its export value evenly across those N_k industries. $Weight_{ij,2017}$ represents the employment share of workers with occupation i , working in industry j, based on 2017 ACS survey data.

[15]Export data for China's city product level, the latest year available is 2016.

D Lagged Effects of Tariffs on Occupations

The impact of the U.S.-China trade war affected companies within target industries, necessitating some time for firms to adjust their labor market approach. In this robustness check, we examine the effects of tariffs lagged by 1 to 6 months on the number of job postings and average wages offered. The results are presented in Appendix Table D1 and Table D2. For affected occupations demand, tariffs do not have a significant negative impact on non-R&D positions. However, the demand for affected R&D positions are significant increase. This positive effect continues to persist and intensify in four months, suggesting that as the trade war rages on, companies' demand for R&D talent becomes increasingly stronger. Regarding occupation wages, starting from the first month affected by tariff, wages for non-R&D positions experience a significant decline. In contrast, wages for R&D positions increase significantly compared to those for non-RD positions.

Table D1 Lagged Effects of Tariffs on Log Job Postings

Log(Postings)	(1) L1.Tariff	(2) L2.Tariff	(3) L3.Tariff	(4) L4.Tariff	(5) L5.Tariff	(6) L6.Tariff
Tariff	-6.448	-6.228	-5.414	-7.694*	-4.008	-0.175
	(4.663)	(4.671)	(4.572)	(4.448)	(4.299)	(4.091)
Tariff $\times$ R&D	11.751**	14.040***	13.661***	15.814***	8.637*	2.748
	(5.047)	(5.246)	(4.847)	(4.680)	(4.440)	(4.754)
Controls	Y	Y	Y	Y	Y	Y
City-Year-Month FE	Y	Y	Y	Y	Y	Y
Occupation-Year-Month FE	Y	Y	Y	Y	Y	Y
City-occupation FE	Y	Y	Y	Y	Y	Y
Observations	808,453	795,858	789,074	783,878	781,164	779,742
R-squared	0.998	0.998	0.998	0.962	0.964	0.966

Notes: This table reports the impact of tariffs on job postings across different lag periods. The sample is Chinese city-occupation level monthly job posting data from January 2017 to June 2020 and monthly city-occupation level tariffs from January 2017 to December 2019. The dependent variable is the city-occupation level number of job postings. The independent variables are city-occupation weighted average tariff exposures lagged by 1-6 months, corresponding to columns (1)-(6), respectively. The city-occupation level tariffs are the weighted average of HS6 product-level tariffs on Chinese exports, with the weights taking into account the share of HS6 products exported by cities to all partners, as well as the distribution of various occupations in different industries. The methodology for calculating weighted average Chinese tariffs at the city-occupation level follows the same logic, which is used as a control variable. Each column includes the interaction of tariff exposure with an R&D dummy variable. The R&D dummy equals 1 if the occupation is classified under the "Research, Development, Design, and Practitioners; Technologists and Technicians" category within the STEM occupation list on the O*NET website, and 0 otherwise. All regressions include city-year-month fixed effects, occupation-year-month fixed effects, city-occupation fixed effects and Chinese tariffs. Standard errors are clustered at the city-month level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D2 Lagged Effects of Tariffs on Log Wages

Log(Wage)	(1) L1.Tariff	(2) L2.Tariff	(3) L3.Tariff	(4) L4.Tariff	(5) L5.Tariff	(6) L6.Tariff
Tariff	-4.070***	-3.830***	-4.291***	-4.056***	-3.820***	-3.466***
	(0.996)	(0.982)	(1.036)	(1.080)	(1.095)	(1.096)
Tariff $\times$ R&D	2.284*	2.161*	2.772**	3.105**	3.252**	2.932**
	(1.247)	(1.241)	(1.293)	(1.356)	(1.348)	(1.295)
Controls	Y	Y	Y	Y	Y	Y
City-Year-Month FE	Y	Y	Y	Y	Y	Y
Occupation-Year-Month FE	Y	Y	Y	Y	Y	Y
City-occupation FE	Y	Y	Y	Y	Y	Y
Observations	738,685	725,366	718,086	712,753	711,176	709,891
R-squared	0.915	0.918	0.921	0.856	0.858	0.857

Notes: This table reports the impact of trade war tariffs on wages across different lag periods. The sample is Chinese city-occupation level monthly job posting data from 2017:1 to 2020:6 and monthly city-occupation level tariff exposure from 2017:1 to 2019:12. The dependent variable is city-occupation level average wages. The independent variable is the city-occupation level average tariff exposure lagged by 1-6 months, corresponding to columns 1-6, respectively. The city occupation level tariffs are the weighted average of HS6 product-level tariffs on Chinese export, with the weights taking into account the share of HS6 products exported by cities to all trade partners, as well as the distribution of various occupations in different industries. The methodology for calculating the weighted average Chinese tariff at the city-occupation level follows the same logic, which is used as a control variable. Each column includes the interaction of tariff exposure with an R&D dummy variable. The R&D dummy equals 1 if the occupation is classified under the "Research, Development, Design, and Practitioners; Technologists and Technicians" category within the STEM occupation list on the O*NET website, and 0 otherwise. All regressions include city-year-month fixed effects, occupation-year-month fixed effects, city-occupation fixed effects and Chinese tariffs. Standard errors are clustered at the city-month level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.