Technological Rivalry and the Allocation of Talent: Evidence from China's College Admission [*]

Xiaohua Bao[†] Qin Chen[‡] Zibin Huang[§] Lei Li[¶] Mengyuan Wang[||]

February 22, 2026

Abstract

This paper studies how the U.S-China technology rivalry reshapes college admissions across fields of study using novel college admissions data and job posting data from China. Exploiting differential exposure to tariff escalation and export restrictions across major-region pairs over time, we find that more exposed pairs experience larger increases in admissions selectivity and enrollment, particularly for STEM majors and elite universities. A one percentage point increase in the tariff exposure raises admission cutoff scores by 2-3 percent. Labor market returns shift in the same direction, with rising wage premia for STEM-related and R&D-intensive positions, consistent with a defensive-innovation channel in which rivalry pressure spurs self-reliance and innovation effort in China, increasing demand for science and high-end engineering skills.

Keywords: Trade War, Field of Study, Return to STEM

JEL Codes: F14, F16, I23, J24

[*]We wish to thank George Alessandria, Miren Azkarate-Askasua, Yan Bai, Corina Boar, Shu Cai, Antonio Ciccone, David Dorn, Wei Huang, Ruixue Jia, Lisa Kahn, Le Kang, Harry Li, Ming Li, Xiaoyan Lei, Xuyan Lou, Ronni Pavan, Zhan Qu, Yuta Suzuki, Junjie Tang, Zi Wang, Yaowu Wu, Han Ye, Nicolas Ziebarth for their comments and suggestions. Support by the German Research Foundation (DFG) through CRC TR 224 (Project B06) at the University of Mannheim is gratefully acknowledged. Huang acknowledges financial support from the National Natural Science Foundation of China (Grant No. 72403152). Bao acknowledges support from National Natural Science Foundation of China (Grant No. 72473095), Shanghai Science and Technology Commission Soft Science Research Project (Grant No. 24692116200), and Marxist Theory Research and Development Project (Grant No. 2024MZD032). We thank Yishu Li for her excellent research assistance. All errors are ours. The first draft of this paper was released in April 2024.

[†]College of Business, Shanghai University of Finance and Economics, xhbao369@mail.shufe.edu.cn

[‡]Metro Data, qinchen1986@hotmail.com

[§]College of Business, Shanghai University of Finance and Economics, and Shanghai Institute of International Finance and Economics, huangzibin@mail.shufe.edu.cn

[¶]Faculty of Business and Economics and Faculty of Humanities, University of Göttingen, lei.li@uni-goettingen.de

[||]College of Economics, Hebei University of Economics and Business, wangmengyuan@163.sufe.edu.cn

1 Introduction

Geopolitical rivalry increasingly plays out through technology and supply chains. When access to foreign markets, critical inputs, and frontier technologies becomes uncertain, the expected returns to different skills can shift accordingly, re-sorting students across fields of study. Despite a large literature on the determinants of major choice (Altonji, 1993; Wiswall and Zafar, 2015; Altonji, Arcidiacono, and Maurel, 2016), we have limited evidence on whether geopolitical tension changes the formation of human capital at scale. Related work on trade and education largely focuses on the extensive margin, studying whether trade liberalization affects schooling and college attendance (Atkin, 2016; Li, 2018). We complement this literature by focusing on the intensive margin within college and studying whether geopolitical tension shifts admissions across majors.

This paper examines how the recent escalation in U.S-China technology rivalry has reshaped college admissions across fields of study in China. Using nationwide college admission records, we exploit differential exposure to the trade war across major-province pairs over time and find that more exposed pairs, primarily STEM majors in more exposed regions, experience larger increases in admission cutoff scores and admitted enrollment, with effects strongest at more selective elite universities.[1] Consistent with rising demand for STEM, labor market payoffs also shift in favor of more exposed major-city pairs over the same period: relative returns rise as wages shift toward STEM-related occupations and wage premia rise for R&D-intensive positions. Taken together, these findings align with domestic "defensive innovation": heightened pressure on supply chains and technology access spurs self-reliance policies and greater firm R&D in China, which in turn raises the expected returns to STEM.

We study this research question in the context of China's National College Entrance Exam (NCEE), or *Gaokao*. The system aims to provide a standardized, uniform, and meritocratic benchmark for evaluating students. It ranks students by exam scores and publishes major-specific admission cutoffs and enrollments by university, exam-taker province, track, and year.[2] Because cutoffs are measured on a common within-province score scale, they allow

[1] STEM is an acronym for Science, Technology, Engineering, and Mathematics.

[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 2.3.

within university-province-track-year comparisons of admission selectivity across majors, providing a unified measure of admission competitiveness across 792 detailed majors that is typically unavailable in decentralized admission systems with non-comparable exam regimes. In this paper, we compile a novel dataset covering college admissions at all Chinese higher education institutions from 2017 to 2020, including major-level admitted enrollment and cutoff scores.

To measure trade war exposure, we use two U.S. policy instruments: import tariffs and export restrictions (e.g., entity list designations). While distinct in implementation, both served a common objective of increasing pressure on China's technology develop in strategic sectors, and we treat them as components of a broad rivalry episode. We construct exposure measures using both instruments, but focus on tariffs in the baseline because they fit our empirical design particularly well: (i) tariffs vary continuously at the HS-10-digit level, delivering substantially richer variation across products; (ii) this granularity allows a cleaner and more transparent mapping from affected products to industries and then to fields of study, supporting heterogeneity analyses; and (iii) tariffs admit a symmetric mirror control using China's retaliatory tariffs, which we construct analogously and include to net out China's trade policy changes.[3]

Our identification strategy uses an exposure design that maps U.S. policy escalation from affected products to provinces and then to detailed majors. We construct a province-major-time tariff shock by starting from HS-10-digit U.S. tariff changes and aggregating them using pre-period export shares, a product-industry concordance, and major-industry employment linkages. This yields a continuous measure of rivalry pressure at the province-major-year level. We construct an analogous province-major measure for China's retaliatory tariffs and include it as a control to net out China's tariff changes.

Our main finding is that tariff escalation is followed by a marked rise in admissions competitiveness for high-exposure majors, especially STEM: cutoff scores increase and admitted enrollment shifts toward these majors, with effects concentrated in elite universities. Quantitatively, a one percentage point increase in the export-weighted tariff imposed across all

[3] By contrast, export restrictions are discrete and firm-based; once aggregated to province-major level they are sparser and potentially more affected by firm-level selection, so we use them primarily as a complementary proxy that validates the technology-rivalry interpretation.

trade partners raises standardized admission cutoffs (mean 0, s.d. 1) by about 2-3 percent, equivalent to roughly a 393-place improvement in rank out of 140,329 NCEE exam takers per province-track-year. This increase is driven primarily by STEM (with little response in fields such as economics) and is strongest at nationally elite universities, weaker at local elite colleges, and absent for ordinary colleges. Using entity list based export restrictions as an alternative proxy for rivalry intensity and technology-containment pressure yields consistent patterns. Our data capture equilibrium admissions outcomes, cutoffs and admitted counts, reflecting both applicant pressure and program capacity. Overall, the evidence is consistent with a defensive innovation channel in which rivalry pressure spurs self-reliance and innovation effort, raising demand for science and high-end engineering training, particularly along elite-university pathways into innovation-oriented careers.

A key identification concern is that our exposure measure may be correlated with pre-existing industrial policies or with differential trends across provinces and broad fields of study. Specifically, Chinese students' major choices may have been influenced by industrial policies implemented prior to the trade war. Meanwhile, the U.S. tariffs may strategically targeted industries already favored by industrial policies. We address this concern in three ways. First, we include rich fixed effects, most importantly province-major-year fixed effects, to absorb time-varying local industrial policy, macro shocks, and other province-specific changes that could differentially affect field of study. Second, we estimate event-study specifications and find no evidence of differential pre-trends prior to the trade war. Third, to mitigate the above concerns, we conduct robustness checks by excluding the effect of "Made in China 2025" which helps isolate the effects of pre-trade war industrial policies; the results remain robust.

To explore the mechanism on how geopolitical shocks reallocate talent across fields of study, we use micro-level online job posting data from 1.13 million firms across 220 job positions and 266 industries, to study the impact of trade war on labor demand for STEM. First, we estimate the impact of the U.S. tariff on wage of different majors in China. It shows that when many other majors experienced declines in labor market return, wages for STEM majors were increased. Second, we apply a similar exposure design method to construct prefecture-occupation-month-level tariff exposure 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, and 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; Smeets, Tian, and Traiberman, 2025; Khanna et al., 2025). 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, 2025). We extend the literature by highlighting a novel mechanism, defensive innovation under geopolitical rivalry, and bringing new evidence using uniquely granular admissions data and job posting data. We show that trade protectionism can reweight the demand for skills, reshaping major-specific admissions.

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 on trade flows and pass-through (Amiti, Redding, and Weinstein, 2019; Fajgelbaum et al., 2020; Jiao et al., 2024; 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 examine how the trade war reshapes human capital formation on the intensive margin by reallocating students across college majors. Rather than asking whether trade war affects schooling or college entry, we study how geopolitical and technological rivalry changes major-specific admissions selectivity and enrollment. We find that tariff shocks paradoxically pushed elite students toward high-tech fields. This pattern aligns with evidence that U.S. tariffs sought to undermine China's high-tech sectors (Bai, Jin, and Lu, 2025; Ju et al., 2024). In response, firms increased R&D, while the government elevated technological self-reliance in strategic industries, accelerating domestic innovation (Yang et al., 2022). These forces plausibly raised returns to STEM and R&D-intensive occupations, tightening admissions competition in high-tech majors.

Third, this paper contributes to the body of research on the determinants of major choice. 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; Blom, Cadena, and Keys, 2021; Conlon, 2021). In this paper, we underscore the role of geopolitical tension in shaping college admission across majors.

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

2 Background

In this section, we document three stylized facts. First, a central objective of the U.S. trade war has been to curb China's advancement in high-tech manufacturing. Second, the relative returns to STEM rose during the trade war period. Third, high-tech engineering majors became increasingly selective relative to other fields over the same period.

2.1 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.

One of the main objectives of the U.S. government in the trade war is to contain the development of high-tech manufacturing industries in China. The imposed tariffs primarily targeted high-tech products, despite their relatively small share of total imports (Ju et al., 2024; Bai, Jin, and Lu, 2025; Feng, Han, and Li, 2023). As shown in Figure 1, the first wave of tariffs concentrated on high-tech manufacturing industries such as electrical equipment and computers & electronics. 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, 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.

2.2 Labor Market Responses

Competition for talent is crucial to technological rivalry. The trade war between the U.S. and China severely hit Chinese manufacturing firms and threatened global supply chains. Firms realized that they would lost their competitive edge if the trade war escalated further. In response, many Chinese firms adopted a strategy of defensive innovation by increasing investment in technology. They raised R&D expenditures and elevated talent strategies to a top managerial priority.[4] The surge in firms' demand for talent was rapidly transmitted to the labor market, increasing labor market returns for related majors.

Figure 2 illustrates average wages across different disciplines using online job posting data. We find that from 2017 to 2021, despite the intensification of the trade war and the overall slowdown of economic growth in China, engineering majors experienced wage increases. In contrast, graduates from all other disciplines—especially economics and the social sci-

[4]For example, in June 2019, Huawei launched the "Young Geniuses" program, offering exceptional young talents salaries of at least five times the national average, with a maximum annual salary of CNY 2 million (USD 285,000), to recruit top innovators.

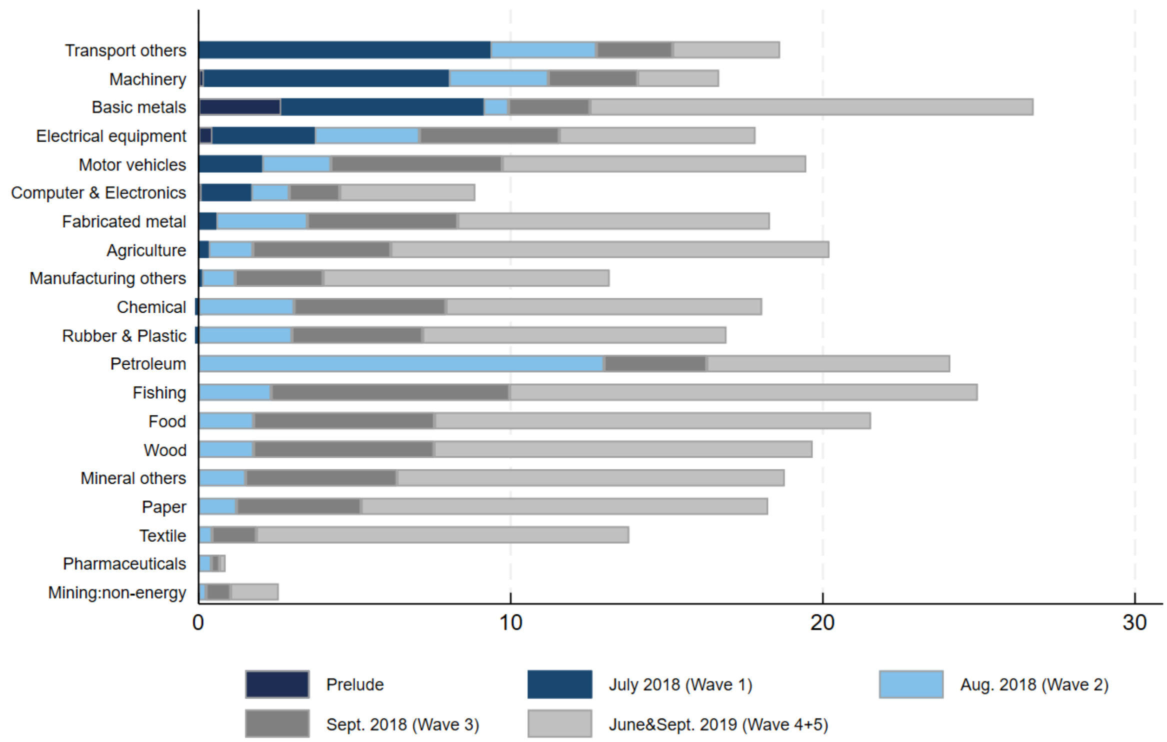

Figure 1 Punitive import tariffs imposed by the U.S. (%)

Notes: This figure shows the distribution of the U.S. tariffs across industries. The tariffs are computed as the weighted average using U.S. imports from China in 2017. Prelude refers to the U.S. imposing tariffs on Chinese imports in February and March 2018.

Source: The United States Census Bureau, the United States Trade Representative (USTR), and the United States International Trade Commission (USITC).

ences—suffered wage declines. We will illustrate more evidence on the Chinese labor market responses across majors and occupations in the following sections.

2.3 College Enrollment in China

The Gaokao, formally known as the National College Entrance Exam (NCEE), is administered once a year and is widely regarded as China's highest-stakes standardized test. High school students sit the exam in their home provinces, and their college admission outcomes depend on their scores. The enrollment process typically has three steps: exam, application, and university admission. While the Ministry of Education (MOE) sets the overarching rules and timeline, provincial education authorities implement the system and may differ in operational details, generating cross-province variation in procedures.

The exam stage requires students to write the NCEE based on their chosen high school

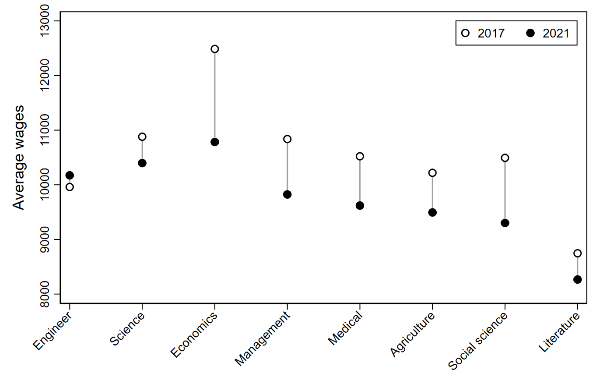

Figure 2 The Return to Major and the Change of Average Wage across Major

Notes: This figure documents how wage evolved across majors from 2017 to 2021. All wages are denominated in RMB.

Source: Wage data from Chinese online recruitment platform *Qian Cheng Wu You* 51*job.com* (http://www.51job.com).

track, which includes the liberal arts, science, and comprehensive tracks. Tracks determine the subjects students have to take in the exam. Since exams are administered at the provincial level, scores are comparable only for students from the same year, province, and track. 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, which makes Chinese students to be very cautious in choosing majors during the application. Second, during the application and admission stages, the NCEE utilizes a "parallel mechanism", which is strategy-proof (Chen and Kesten, 2017; Bo et al., 2019; Yang, 2024). All university-major combinations are divided into 3 batches and the admission process run by order from the first batch to the third, corresponding to the best to the lowest-ranked schools. Third, "university-major" enrollments (quotas) are limited at the province level. The score of the last admitted student for a specific "university-major" combination serves as the cutoff admission score.

Figure 3 shows the changes of the standardized admission scores across major categories from 2017 to 2021. It is clear that science and high-tech engineering majors became more and more selective relative to other majors, especially after 2018 when China was involved in the trade conflict with the U.S.

2.4 Trade War, Labor Market, and Major Allocation

In general, we identify three key patterns during the U.S.–China trade war. First, the U.S. targeted high-tech industries in China. Second, Chinese firms increased their labor demand for STEM-related majors. Third, admission scores for STEM-related majors rose significantly. We will show that these patterns are not coincidental. Rather, they reflect a defensive innovation response by Chinese firms to heightened risk and urgency, which attracted more students to choose STEM-related majors and, in turn, pushed up their admission scores.

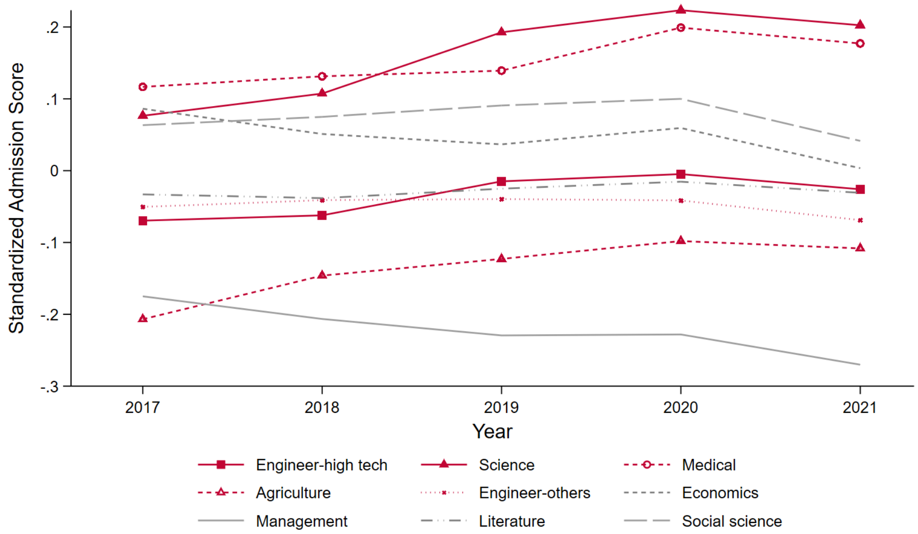

Figure 3 The NCEE Admission Score across Major

Notes: This figure shows the evolution of admission scores across 2-digit major categories in China's National College Entrance Examination (NCEE) from 2017 to 2021. The vertical axis reports standardized admission scores. For each 2-digit major category, the standardized admission score is constructed as the enrollment-weighted average of standardized scores across all majors (6-digit) under that category. The red series corresponds to sciences, engineering(high tech and others), medical, and agriculture. The gray series corresponds to economics, management, literature, medicine, and social sciences. High tech engineering refer to majors such as mechanical engineering, micro-electromechanical systems (MEMS) engineering, precision instrumentation, electronics and information engineering, and artificial intelligence. The social sciences group further comprises major categories including philosophy, law, education, history, and arts.

Source: The university enrollment data from official application guidance documents across various provinces.

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 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" of the national MOE. These universities have extensive histories and nationally esteemed reputations. Local elite universities, or *shuangfei yiben*, usually 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. As depicted in Table 1, Panel A, the ordinary university admits an average of 1,729 new students across 26 majors annually. Elite universities tend to enroll a greater number of students 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

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.

the fierce competition students face in selecting majors, where only those with higher scores can secure admission to popular programs.

3.2 Tariff and Trade Data

In this section, we first describe the data collection of tariff and trade data, and then introduce the construction of the key explanatory variable: province–major–specific tariff. Additional details are provided in Appendix B.

3.2.1 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 collect the monthly *tariffs faced by Chinese products* exported to the U.S. from the United States International Trade Commission (USITC) and the United States Trade Representative (USTR) announcements. Second, we collect the monthly *retaliatory import tariffs imposed on Chinese imports of American products* from the General Administration of Customs China and the Ministry of Finance of China. Third, we also collect the *tariffs faced by Chinese products exported to other countries and the tariffs imposed on products imported from other countries to China* from the United Nations Conference on Trade and Development (UNCTAD) database and the Ministry of Finance of China. 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.

We draw on the import and export data from China's General Administration of Customs in 2017 to construct the weights in calculating each major's exposure to the tariffs. This dataset records every transaction made by Chinese enterprises, encompassing the product HS code, product value, product quantity, and import source (or export destination) country.

3.2.2 Trade Shock

Our identification strategy relies on converting the product level tariff shock to major level tariff shock, which is constructed as the weighted average tariff faced by Chinese exporters in the industries associated with each major. To verify the robustness of the empirical results, we construct two sets of tariff shocks: (i) province-major-level tariff, and (ii) major-level tariff that is common across provinces. The construction proceeds in three steps as shown in Figure 4.

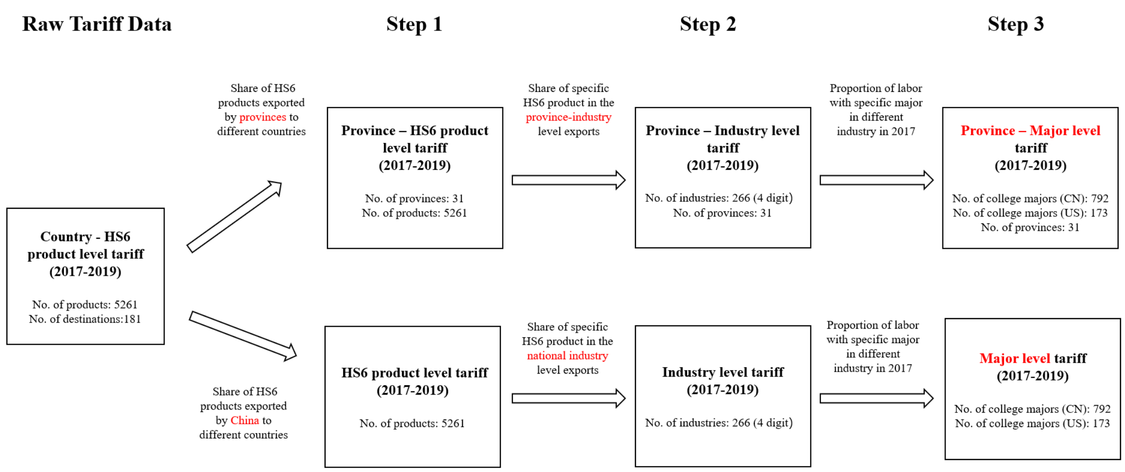

Figure 4 Method for Calculating National and Provincial Major Tariff

Province-major-level tariff shock. To construct province-major-level tariff shock, first, we compute the average tariff faced by each province-HS6-product pair as an export-share-weighted average across export destination countries, using province-specific destination shares in 2017 as weights. Intuitively, provinces that exported a larger share of a given product to the United States before the trade war are more exposed to U.S. tariff changes on that product. Second, we aggregate province-product exposure to the province-industry level using the product-to-industry concordance in Pierce and Schott (2012) and the export share of each HS6 product within each industry. Third, we map industries to majors based on the industry distribution of college graduates by major. Specifically, we use American Community Survey (ACS) data to obtain major-by-industry employment shares and use these shares to convert province-industry exposure into a province-major tariff shock.[5] Appendix Section B provides a detailed description of the data, variable construction, and shift-share diagnose tests.

To net out concurrent China-side trade policy changes, we construct an analogous Chinese retaliatory tariff measure using the same mapping logic and include it as a control in the main specifications. This control is also defined at the province–major–year level, providing a symmetric adjustment for China-side tariff movements.

Major-level Tariff Shock. For major-level tariff shock, the construction process is similar to the province-major-level one. We implement Steps 1–3 (see Figure 4), but do not exploit cross-province differences in sensitivity to U.S. tariff changes. Specifically, we combine (i) the distribution of China's exports of specific HS6 product across destination countries, (ii) product shares in China's exports within specific industry, and (iii) the cross-industry employment distribution of labor with specific major based on the 2017 ACS survey. Aggregating these components yields a national major tariff.

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. 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 transactions—including exports, re-exports, or domestic transfers—with entities on the list are subject to stringent

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

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 match 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 300 million recruitment entries posted on *Qian Cheng Wu You* 51*job.com* (hereafter, 51job.com) platform from 2017 to 2020, which is one of the largest Chinese online recruitment platform. 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 vacancies, job titles, job descriptions, company names and profiles, job locations, posting dates, and wages. This data is aggregated by month. To enable occupation-level analysis, we further map each posting to a six-digit 2018 Standard Occupational Classification (SOC) code using an LLM-assisted workflow that builds and validates a job title-to-SOC dictionary. The resulting data span 220 detailed occupations across 22 SOC major groups. Appendix C provides more details.

3.5 Descriptive Analysis

3.5.1 Tariff across Majors

Figure 5 illustrates the impact of tariff shocks on various major disciplines in China. The tariff shocks are defined by differencing tariffs between December 2019 and December 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 (2025), 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 college admission. We draw a bin scatter plot (each dot includes various province-college-major observations) in Figure 6 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 5) 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 A4). In particular, they are concentrated in fields such as mechanical engineering, material sciences, and electronic information.

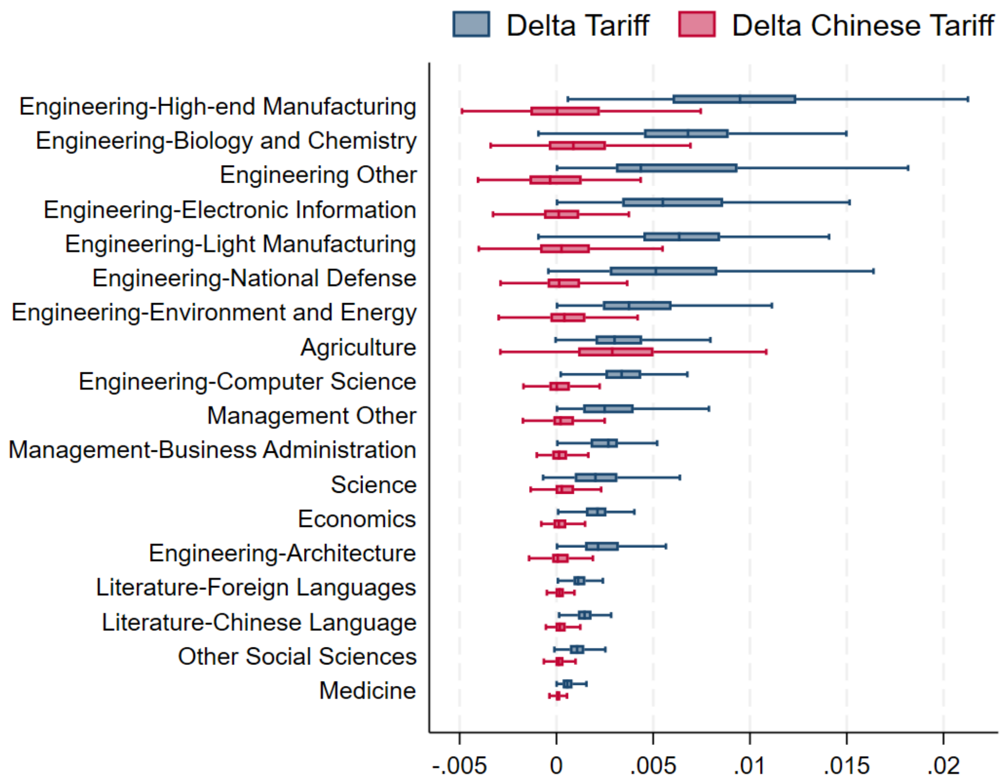

Figure 5 Tariff Shock on Disciplines in 2017-2019

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

4.1 Baseline Regression

In our baseline regression, we investigate how the tariff shocks from the U.S.-China trade war affect college admission across majors. We estimate the following empirical model:

$$Y_{ipsbmt} = \alpha + \beta_1 \tau_{pm,t-1} + \beta_2 \tau^{CHN}_{pm,t-1} + \delta_{it} + \mu_{Mt} + \gamma_{ipsM} + \varepsilon_{ipsbmt} \quad (1)$$

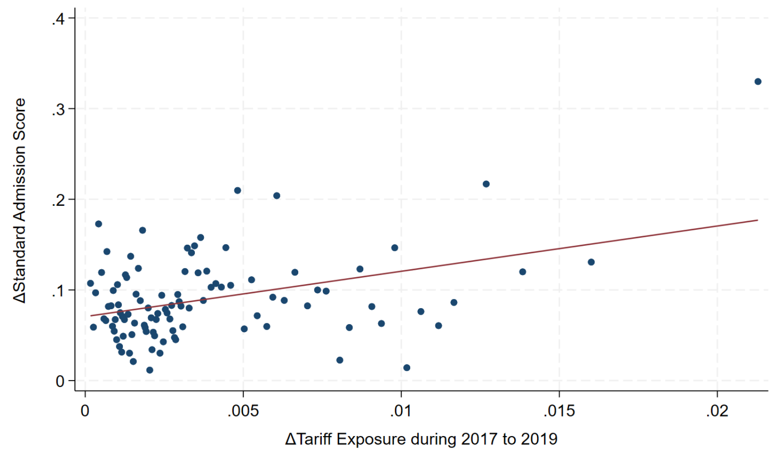

Figure 6 Tariff Exposure and Admission Score

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, b, m, t denote the college, applicant's province, NCEE track, batch, 6-digit major, and time, respectively.[6] Y_{ipsbmt} denotes the standardized admission score cutoff (calculated within province-year-track clusters, mean zero, s.d. one) for major m, university i, in applicant's province p, track s, batch b, and year t. This is the minimum score required for admission to the university-major pair in a specific province and track 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. $\tau_{pm,t-1}$ 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.) $\tau^{CHN}_{pm,t-1}$. We further control for the enrollment number of the university-major combination for a specific province in a given

[6]Although the admission batch is primarily determined at the college level, there are a few cases in which a single college offers majors across different batches. In some rare instances, even the same major within a college may have distinct class types (e.g., international versus ordinary classes) that recruit students in different batches. Consequently, there exists variation in the score variable at the *ipsbmt* level.

year. There are several sets of fixed effects in the baseline regression setting, including college-year-level (it), major category-year-level (Mt), and college-province-track-major category-level ($ipsM$). m refers to detailed 6-digit major and M refers to 2-digit major category. We also try to control for more detailed fixed effects as robustness checks, including province-track-year-level (pst), province-major category-year-level (pMt), and college-province-batch-year-level ($ipbt$) fixed effects. The conclusion is not changed. We will discuss the purpose of adding these fixed effects in the following section. We estimate this regression using the number of admitted students as weights, which assigns greater influence to majors with larger enrollment and helps suppress noise from small-sample cells. Standard errors are clustered at the province-major level.

4.2 Identification Issues

Our empirical strategy faces several identification concerns. One concern is that raw NCEE scores are not directly comparable across provinces and years, because provincial education examination authorities independently design, administer, and grade the exam. We address this issue in three ways. First, we standardize admission cutoff scores within each province-track-year so that each cutoff is interpreted relative to the local distribution of college-major cutoffs, capturing a major's relative competitiveness within the local choice set. Second, we additionally use score percentiles at province-track-year level as the outcome. Third, we include province-track-year fixed effects in specifications with more detailed fixed effects; the results remain unchanged.

The second concern is the confounding industrial policies. If, prior to the U.S.–China trade conflict, a province fostered a structural preference for specific discipline through industrial planning, fiscal subsidies, or flagship projects, such policy shocks could co-move with tariff changes and generate omitted-variable endogeneity. We address this concern in four ways. First, in the baseline regression, we include major category-year fixed effect to absorb overall trend across majors categories induced by national industrial policies. We further include province-major category-year fixed effects in the regression with more detailed fixed effects. Rely on the fixed effects, identification comes from within province-major category-year variation across narrow majors induced by heterogeneous exposure to U.S. tariffs. Provincial policies typically do not operate at the detailed 6-digit major level. Second, we control for each major's exposure to China's import tariffs, recognizing that during the trade conflict China adjusted retaliatory (or protective) tariffs on the United States and MFN tariffs on other countries, which helps purge score fluctuations attributable to Chinese tariff changes. Third, in robustness checks we include controls for contemporaneous policy shocks—specifically, the Made in China 2025 initiative and AI-related technological shocks. These policies do not qualitatively alter our estimated effects. Fourth, we conduct a pre-trend analysis using an event study design in Section 5.1 to ensure that the differences in test score trajectories across majors did not exist prior to the trade war due to any pre-existing industrial policies.

The third concern is that the change of admission quotas and admission rules can distort the relationship between tariffs and admission score. The observed cutoff is the equilibrium price of major demand conditional on the college-major quota. If a trade shock raises a major's attractiveness and the college expands its quota, the resulting increase in supply tends to lower the cutoff, potentially attenuating the observed demand-driven response. We address this concerns in two ways. First, in the baseline regression, we control for college-year and major category-year fixed effects to absorb overall changes in admission quotas across colleges and major categories. We further try to include college-province-batch-year fixed effects. These more detailed fixed effects absorb supply-side factors. Second, we examine the supply margin by using the enrollment number at the province-college-track-major level as the dependent variable to assess how trade shocks affect quotas.[7] We find that colleges have significantly expanded enrollment of affected majors, implying that estimates based on admission score are conservative (downward-biased in magnitude), which strengthens our conclusion. We also run a set of regression by controlling for the enrollment quotas directly and our main conclusions are not changed. We decide not to show the results in the paper because it suffers from the bad control problem. The results are available upon request.

[7]Because original quota data are unavailable, we proxy quotas with final admits. Under the NCEE system, enrollment plans are strictly enforced, so the final number of admits generally equals the planned quota, making this a reliable proxy.

5 Main Results

5.1 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. To address this concern, we use an event study regression to visualize the effect of tariff exposure on college admission scores in different years. 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:

$$Y_{ipsbmt} = \alpha + \sum_{q=-2}^{4} \beta_q I(event_q) \times \Delta\tau_{pm} + \sum_{q=-2}^{4} \gamma_q I(event_q) \times \Delta\tau_{pm}^{CHN} + \delta_{it} + \mu_{Mt} + \gamma_{ipsM} + \varepsilon_{ipsbmt} \tag{2}$$

$\Delta\tau_{pm}$ represents the province-major level tariff surge in Dec. 2019 relative to that of Dec. 2017, and $\Delta\tau_{pm}^{CHN}$ 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 U.S.-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. We control for the same set of fixed effects as in the baseline regression.

Figure 7 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.

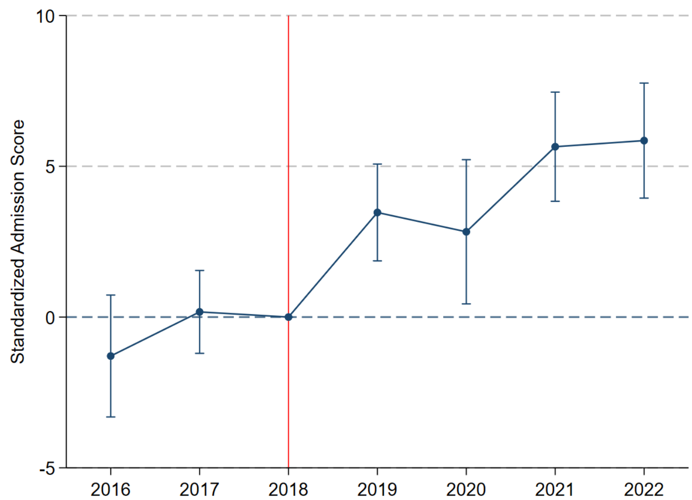

Figure 7 Event Study of Tariff Effect on Admission Score

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-batch-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 college-year, major category-year and province-college-track-major category fixed effects. Major category level fixed effect refers to 2-digit major. The interactions between Chinese tariff increase and each year dummies are included as control variables.The regression is weighted by province-college-track-batch-major-year level enrollment. The estimate include 95% confidence intervals, where standard error is clustered at the province-major 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.

5.2 Baseline Result

Table 2 displays the positive impact of 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. Our baseline result in column (1) shows the results of our baseline regression setting. We find that 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. We add more detailed fixed effects in columns (2) and (3) and the results are robust. 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. The results are unchanged if we construct the tariff shock only considering tariffs between the U.S. and China, as shown in Appendix Section E.4.

Table 2 Baseline Results

Standardized Admission Score	(1)	(2)	(3)	(4)	(5)
Tariff	3.597***	2.534***	1.820***	1.545**	0.526
	(0.877)	(0.914)	(0.624)	(0.672)	(0.787)
Tariff × Nation Elite College				1.803**	2.773***
				(0.739)	(0.850)
Tariff × Local Elite College					2.129**
					(0.857)
Controls	Y	Y	Y	Y	Y
College-Year FE	Y	N	N	N	N
Major Cat-Year FE	Y	N	N	N	N
Prov-College-Track-Major Cat FE	Y	Y	Y	Y	Y
Prov-Track-Year FE	N	Y	Y	Y	Y
Prov-Major Cat-Year FE	N	Y	Y	Y	Y
Prov-College-Batch-Year FE	N	N	Y	Y	Y
Observations	925,332	925,332	925,332	925,332	925,332
R-squared	0.925	0.923	0.969	0.969	0.969

Notes: This table reports the results of the main regression. The dependent variable is standardized admission scores at the province-college-track-batch-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 enrollment at the province-college-track-batch-major-year level. Column (1) includes college-year, major category-year and province-college-track-major category fixed effects. Column (2) additionally includes province-track-year and province-major category-year fixed effects. Column (3) further includes province-college-batch-year fixed effect. Column (4) and (5) add interaction terms between the tariff and college type dummies. *National elite college* refers to universities sponsored by the 211 Project, which roughly corresponds to the top 100 universities in China. *Local elite college* refers to universities in the first batch of the admissions process but not sponsored by the 211 Project. Major category level fixed effect refers to 2-digit major. The province-major-year level Chinese tariff on foreign imported products and its interactions with elite university dummies are included as control variables in all columns. Standard errors are clustered at the province-major level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The main results may appear to be 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.

We further show the impact of the Tariff on the enrollment quota. Columns (1)-(3) of Table

D1 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 a one percentage point increase in the weighted average tariff imposed by all trade partners on China leads to a 3 percent increase in the enrollment quota, suggesting that the Chinese government aimed to develop human capital in targeted fields to compete with the U.S.. We provide more detailed discussion in Appendix Section D.

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 offset the expected decline in labor demand and wages intended by the tariff shock. Instead, the affected fields gained more wage premium and public attention. In the following sections, we will present more evidence supporting this mechanism.

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 development. 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 column (4) and (5) of Table 2.[8] We include interaction terms between the tariff shock and *National Elite* and *Local Elite*. *National Elite* indicates whether a college is sponsored by the 211 Project, and *Local Elite* denotes whether a college is part of the first batch of colleges but not sponsored by the 211 Project. Table 2 shows that the positive effect of higher tariffs on admission scores

[8]We show the results of the regression with the most detailed fixed effects in the main context. All the results are robust when we change the set of fixed effects.

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 5.43 percentage point increase in the standardized admission score in national elite colleges and 2.66 percentage point in local elite colleges. Table D1 further shows similar results for enrollment quota. 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.

5.4 STEM and Non-STEM Majors

As shown in Figure 5, 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 3 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 affected 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 3 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 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.

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 (EL). To further alleviate concerns that tariffs may not ade-

Table 3 Tariffs and Admission Scores Across Major Categories

Admission Score	(1) Engineering	(2) Science	(3) Administration	(4) Economics	(5) Literature	(6) Agriculture
Tariff × Nation Elite College	2.283***	8.019*	-5.352	43.275	17.150	-1.390
	(0.757)	(4.297)	(3.755)	(39.228)	(15.530)	(2.090)
Tariff	-0.318	0.665	-2.402	-46.540**	-16.093*	2.192*
	(0.611)	(3.163)	(1.529)	(22.306)	(9.066)	(1.308)
Controls	Y	Y	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y	Y	Y
Province-College-Track FE	Y	Y	Y	Y	Y	Y
Province-College-Batch-Year FE	Y	Y	Y	Y	Y	Y
Observations	359,511	67,846	176,206	59,015	99,864	16,850
R-squared	0.969	0.971	0.960	0.971	0.969	0.976

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 province-college-track-batch-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 *National Elite College* dummy. We run the regression separately for different major categories. Major categories with too few observations are excluded from the table, including philosophy, history, art and medicine. After controlling for the detailed fixed effects, the variation of the data barely remains for these categories, which leads to huge standard errors. The sample spans the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-batch-year level. We control for province-track-year, province-college-track, and province-college-batch-year fixed effects in all columns. The province-major-year level Chinese tariff on foreign imported products (and its interactions with elite college dummies) are included as control variables in all columns. Standard errors are clustered at the province-major level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

quately 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:

$$Export\_control_{pjt} = \sum_{i \in j,p} Y_{pijt} \cdot \mathbf{1}(EL = 1) \tag{3}$$

i, j, t denote firm (on the entity list), industry, and year. Y_{pijt} is the log of firm registered capital or number of employees, thereby capturing heterogeneity in firm size. $\mathbf{1}(EL = 1)$ is the indicator function representing whether Chinese firm i in province p, industry j was designated on the U.S. entity list in year t. Then, we map the export controls from the province-industry level to the province-major level.

$$Export\_control_{pmt} = \sum_{j} Weight_{jm,2017} \times Export\_control_{pjt} \tag{4}$$

$$Weight_{jm,2017} = \frac{Employ_{jm,2017}}{\sum_j Employ_{jm,2017}} \tag{5}$$

Consistent with equation (14), 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.

Table 4 presents the results using export controls as the measure of U.S.-China technological rivalry. We utilize the aggregated registered capital (columns 1-3) and the total number of employees (columns 4-6) of firms in EL 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. The standard deviation of the export control exposure is 2.59 (asset) and 1.38 (employee). Therefore, for one standard deviation increase of this entity list exposure, the cutoff admission score for that major increases by 2 (asset) and 0.7 (employee) 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 show that U.S. export controls raise admission scores only for related majors at elite universities, particularly at national elite universities.

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. Fourth, we examine the potential contamination from the AI technology shock.

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

Table 4 Alternative Measure: Export Controls

	Standardized Admission Score					
	Export Control (lnAsset)			Export Control (lnEmployee)		
	(1)	(2)	(3)	(4)	(5)	(6)
Export Control	0.008***	0.007**	0.002	0.005	0.003	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Export Control × Nation Elite		0.010**	0.014***		0.014***	0.022***
		(0.004)	(0.005)		(0.004)	(0.005)
Export Control × Local Elite			0.011***			0.020***
			(0.004)			(0.004)
Tariff	1.682***	1.431**	0.520	1.735***	1.503**	0.708
	(0.621)	(0.670)	(0.791)	(0.623)	(0.674)	(0.798)
Tariff × Nation Elite		1.651**	2.516***		1.555**	2.310***
		(0.738)	(0.853)		(0.740)	(0.857)
Tariff × Local Elite			1.886**			1.643*
			(0.861)			(0.867)
Controls	Y	Y	Y	Y	Y	Y
Province-College-Track-Major Cat FE	Y	Y	Y	Y	Y	Y
Province-Track-Year FE	Y	Y	Y	Y	Y	Y
Major Cat-Province-Year FE	Y	Y	Y	Y	Y	Y
College-Province-Batch-Year FE	Y	Y	Y	Y	Y	Y
Observations	925,032	925,032	925,032	925,032	925,032	925,032
R-squared	0.969	0.969	0.969	0.969	0.969	0.969

Notes: This table reports the results of the main regression with export controls as the alternative measure of U.S.-China technology rivalry and the heterogeneous effects of export controls on admission scores across different college types. The dependent variables is standardized admission scores at the province-college-track-batch-major-year level. The main independent variables are the intensity of U.S. export controls imposed on Chinese firms and its interaction terms with two college-type dummies. The *Export Control* variable is measured by the total registered capital of firms (column 1-3), or the total number of employees of firms (column 4-6) at the province-major-year level. *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 covers the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-batch-major-year level. We control for province-college-track-major category, province-track-year, province-major category-year, and province-college-batch-year fixed effects in all columns. 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 is included as control variable in all columns. Standard errors are clustered at the province-major level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 province-major category-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. Second, MIC 2025 was implemented in 30 pilot cities after 2015 (Mane, Park, and Shen, 2025), and we repeat our main analysis excluding colleges in these pilot cities. The list of pilot cities is provided in Appendix Table A3. The regression results without these pilot cities are shown in column (1) of Table 5, 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 5 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 5 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.

Contemporaneous AI Shocks. Technological change and the way it is combined with labor can substantially shape individuals' career plans and thus their choice of college major. In

Table 5 Robustness checks

Admission Score	(1) Pre industry Policy	(2) Pandemic	(3) Drop EL Colleges	(4) Colleges in EL	(5) AI Substitution	(6) Detail AI exposure
Tariff	1.744***	2.073***	1.639**	1.682***	1.900***	1.627*
	(0.668)	(0.675)	(0.645)	(0.639)	(0.665)	(0.654)
Tariff × Entity List College				3.191**		
				(1.272)		
Elasticity to AI Substitution					-0.004	
					(0.006)	
Creativity						0.124**
						(0.043)
Handicraft						0.187***
						(0.042)
Social Skill						-0.093***
						(0.036)
Routine Cognitive Intensity						-0.011
						(0.021)
Routine Manual Intensity						-0.345***
						(0.051)
Controls	Y	Y	Y	Y	Y	Y
Prov-College-Track-Major Cat FE	Y	Y	Y	Y	Y	Y
Prov-Track-Year FE	Y	Y	Y	Y	Y	Y
Prov-Major Cat-Year FE	Y	Y	Y	Y	Y	Y
Prov-College-Batch-Year FE	Y	Y	Y	Y	Y	Y
Observations	637,544	627,085	904,016	925,332	905,578	905,578
R-squared	0.965	0.970	0.967	0.969	0.969	0.969

Notes: This table reports the results of several robustness checks. The dependent variable is standardized admission scores at the province-college-track-batch-major-year level. The independent variable is the weighted average tariff imposed by all buyers of Chinese exports at the province-major-year level. 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 *Entity List College* dummy. To control for AI-related technological shocks, we include province-major-year level AI substitution elasticity in column (5) and five-dimension skill scores at province-major-year level in column (6). The skill scores including creativity, handicraft, social skill, routine cognitive, and routine manual. The sample covers the years 2017 to 2020. All regressions are weighted by enrollment at the province-college-track-batch-major-year level. We control for province-college-track-major category, province-track-year, province-major category-year, and province-college-batch-year fixed effects in all columns. Major category level fixed effect refers to 2-digit major. The province-major-year level Chinese tariff on foreign imports is included as control variable in all columns. Standard errors are clustered at the province-major level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

recent years, computer technologies, led by AI, have achieved notable breakthroughs. If these advances reshaped applicants' preferences across majors and such major-level AI exposure is correlated with tariff exposure, OLS estimates of tariff effects would suffer from endogeneity bias. To mitigate this concern, we draw upon the task-based framework established by Acemoglu and Autor (2011) and control for two sets of AI-exposure measures: (i) AI substitution elasticity (σ) at the major level, which gauges how easily labor in the field can be replaced by computer technologies. Larger values indicate easier substitution (σ>1); values between 0 and 1 indicate limited substitutability (0<σ<1); σ=0 corresponds to perfect complementarity. (ii) Five-dimension skill scores at province-major-year level, including creativity, handicraft, social skills, routine manual, and routine cognitive, extending from Autor and Dorn (2013). Each score is normalized to [0,1], with higher values indicating stronger requirements for the corresponding skill.[9] Table 5 indicates that the tariff-induced effects on admission score remain statistically significant and broadly stable in magnitude after adding AI substitution elasticity in column (2), and including the five-dimension skill scores in column (3).

Other Robustness Checks In Appendix E, 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 control for the effect of students studying abroad. Generally, we find that our results are robust.

6 Mechanism

In the previous analysis, we show that the trade war triggers a clear shift toward STEM in college admissions. We then turn to labor market evidence to clarify the incentives fac-

[9]The construction details of AI exposure are provided in the Appendix G. Based on the city-industry-position-major level job posting data from *Qian Cheng Wu You* 51*job.com* in 2017-2020, we apply AI-based methods to infer task content.

ing college applicants. We show two aspects of evidence. (1) The relative payoff to STEM rises: demand shifts toward science- and engineering-related occupations, and the wage premium for R&D-intensive positions increases relative to non-R&D jobs. (2) The public is more aware of the U.S.-China trade war in locations more exposed to the tariff. These patterns are consistent with a channel in which U.S. trade measures induce innovation-oriented adjustments among Chinese firms, increasing demand for high-skilled talent in affected sectors and thereby strengthening the perceived value of STEM training for students and their families.

6.1 Trade War and Labor Market Return

We first consider the labor market responses using data from "51job.com," a leading recruitment platform for Chinese college graduates. We investigate this issue in two parts: (1) major returns in wages; (2) R&D occupation labor market demand.

First, to estimate the impact of the U.S. tariff on labor market returns of different majors, we aggregate the data to the city-industry-occupation–major-year level and estimate the following model:

$$\begin{aligned} Y_{ijmkt} = {} & \alpha + \beta_1 \tau_{imt} \times Engineering_M + \beta_2 \tau_{imt} \times Science_M + \beta_3 \tau_{imt} \times Econ_M \\ & + \beta_4 \tau_{imt} \times Literature_M + \beta_5 \tau_{imt} \times Agriculture_M + \beta_6 \tau_{imt} \times Medicine_M \\ & + \beta_7 \tau_{imt} \times SocialScience_M + \varphi_{kt} + \delta_{jt} + \mu_{it} + \xi_{jk} + \lambda_m + \varepsilon_{ijmkt} \end{aligned} \tag{6}$$

Here, i denotes city, j refers to SIC-4 digit industry , k represents SOC 6-digit occupation, m denotes major, M is major category (2-digit), and t represents year. The dependent variable measures the average wage for occupation k in industry j of city i, based on job postings that requiring a college degree in major m. We include a set of dummy variables representing different majors. The tariff exposure τ_{imt} is calculated in the same way as in the main regression, except that we use city-level export structures instead of province-level ones.

Column (1) of Table 6 shows that, when we use all other majors as the baseline group, in response to tariff shocks, the average wages for positions requiring science and engineering majors degree are significantly higher than those for other fields. In column (2), we take management as the reference category and include interaction terms between the tariff shock and

Table 6 Tariffs and the Returns to College Major

lnwage	(1)	(2)	(3)	(4)
Tariff × Engineering	3.574***	4.478***	4.493***	4.468***
	(1.214)	(1.563)	(1.560)	(1.565)
Tariff × Science	5.369***	6.234***	6.149***	6.203***
	(2.047)	(2.301)	(2.284)	(2.303)
Tariff × Economics		-7.647*	-7.740*	-7.686*
		(4.244)	(4.238)	(4.250)
Tariff × Literature		7.580	7.718	7.651
		(5.653)	(5.620)	(5.648)
Tariff × Agriculture		3.930**	3.976**	3.931**
		(1.963)	(1.962)	(1.964)
Tariff × Medicine		9.165*	9.296*	9.112*
		(5.104)	(5.114)	(5.116)
Tariff × Social Science		0.323	0.274	0.311
		(7.648)	(7.637)	(7.648)
Tariff	-1.780	-2.926*	-2.950*	-2.919*
	(1.266)	(1.693)	(1.692)	(1.695)
Elasticity to AI Substitution				0.002
				(0.003)
AI exposure (5 dimension)	N	N	Y	N
Control and FEs	Y	Y	Y	Y
Observations	2,083,282	2,083,282	2,083,282	2,083,282
R-squared	0.502	0.502	0.502	0.502

Notes: The dependent variable is the city-industry-occupation-major level yearly average wage, and the independent variable are the interaction between city-major-year level weighted average tariff of Chinese exports and Major category (2 digit) dummy variable. Column (3) includes five skill-intensity measures, and Column (4) includes the AI substitution elasticity. Both sets of AI exposure measures are constructed at city–major level (see Appendix G). All specifications include city-year, occupation-year, industry-year, industry–occupation, and major fixed effects. We also include, as controls, interactions between city-major level Chinese weighted average tariff and the Major category(2 digit) dummy. Regressions are weighted by the city-industry-occupation-major level job posting demand. SSCI include Philosophy, Law, Education, History, Art. Standard errors are clustered at the city-major level. *** p < 0.01, ** p < 0.05, * p < 0.1.

dummies for all other major categories. The results reveal that tariff shocks are associated with significantly higher wages for positions requiring science and engineering degrees relative to those requiring management backgrounds. Given that economics and management graduates are more commonly employed in administrative, managerial, and financial roles, this pattern suggests that firms may reduce expenditures on administrative functions while intensifying demand for STEM talent in as a strategy to enhance resilience and innovation capacity. To account for contemporaneous technology shock, column (3) controls for five-dimension skill scores while column (4) further includes the elasticity to AI substitution. Our main results are not changed.

Second, we show the impact of the U.S. tariff on the labor demand of the R&D-related occupations by runing the following regression:

$$Y_{ikt} = \alpha + \beta_1 \tau_{ik,t-3} + \beta_2 \tau^{CHN}_{ik,t-3} + \varphi_{ik} + \delta_{kt} + \lambda_{ik} + \epsilon_{ikt} \tag{7}$$

Here i, k, t denote the city, occupation, and year, respectively. Y_{ikt} denotes the number of job postings and the average wage for occupation k in city i during period t. $\tau_{ik,t-3}$ and $\tau^{CHN}_{ik,t-3}$ capture the weighted average tariff on Chinese exports and imports for occupation k in city i, respectively, lagged by three months to account for labor market adjustment. The subscript t indicates the year-month. The construction process of this variable is shown in Appendix F. We check the robustness of our results by varying the lag periods, as detailed in Appendix E.9.

Table 7 presents the results. 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. We find that a one percentage point increase in the weighted average tariff correlates with a 13.67 percent increase in job demand and 2.77 percent relative increase in wage for R&D occupation compared to non-R&D Occupation. It shows that the overall job demand for R&D-related occupations increased significantly and the average wages for R&D-related occupations also increased significantly compared to non-R&D occupations (though there is an overall trend of wage decline). This finding explains why only students from elite universities showed a notable increase in their intention to enroll in STEM majors.

6.2 Trade War and Information Transmission

Information transmission plays a key role: only when the labor market changes are perceived by students and their families can it further affect college application and admission. Beyond official media, information also spreads through a sizable ecosystem of NCEE counseling agencies and online influencers in China, who provide college- and major-selection

Table 7 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 × 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

guidance and thereby speed up information transmission. Zhang Xuefeng is a salient example, who has more than 40 million followers as a prominent admissions-advice influencer. After the onset of the trade war, he remarked in a public livestream (see figure H1) that students should "choose majors by following Trump," arguing that majors targeted by Trump could, paradoxically, offer stronger long-run prospects.

We provide the direct evidence on public awareness of the U.S.-China trade war. Using Baidu Index, which is comparable to Google Trends, we focus on two keywords: "U.S.-China trade war (*zhongmei maoyi zhan*)" and "U.S.-China trade friction (*zhongmei maoyi moca*)". 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-level 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:

$$Baidu\ Index_{i,t} = \alpha + \beta_1 \tau_{i,t} + \beta_2 \tau_{i,t}^{CHN} + X_{i,t} + \delta_i + \lambda_t + \epsilon_{i,t} \tag{8}$$

$$\tau_{ik,t} = \sum_{c} \frac{Export_{ick,2016}}{Export_{ik,2016}} \times \tau_{ck,t} \tag{9}$$

$$\tau_{i,t} = \sum_{k} \frac{Export_{ik,2016}}{Export_{i,2016}} \times \tau_{ik,t} \tag{10}$$

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. $\tau_{i,t}$ represents the weighted average of foreign tariffs on exports of city i in month t. We include $\tau_{i,t}^{CHN}$ 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.

Table 8 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8 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.

7 Conclusion

College major choices and admissions matter. They shape students' career trajectories, earnings prospects, job satisfaction, and broader life outcomes. In the aggregate, how students sort across fields determines the supply of skills in the economy, influencing labor-market tightness and the direction of structural change. A large literature studies the determinants of major choice, highlighting expected wages, gendered beliefs, and information frictions, among other forces. Yet we know far less about how college admission respond to technology rivalry.

In this paper, we study the impact of the U.S.-China trade war on college admission across majors by exploring a novel channel, namely defensive innovation. Trade disputes are often about technological rivalry and countries have incentives to influence foreign innovation through trade policies. 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 raises demand for STEM-related majors. Indeed, we find more exposed major-region pairs experience larger increases in admissions selectivity and enrollment, particularly for STEM majors and elite universities. Meanwhile, labor market demand also shift in favor of more exposed major-region pairs over the same period: relative returns rise as wages shift toward STEM-related occupations and wage premia rise for R&D-intensive positions.

Apart from exploring a novel channel, our paper also complements the literature on trade and human capital accumulation. Existing work on trade and education mainly studies the extensive margin (college versus no college); we instead study the intensive margin: how admissions outcomes reallocate across college majors.

Our results highlight the role of technology rivalry in shaping the allocation of skills through labor market incentives. These findings are relevant for policymakers and education institutions concerned with how strategic policy shocks shape human capital development and align educational choices with evolving industry demands.

References

Acemoglu, Daron and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, vol. 4. Elsevier, 1043–1171.

Altonji, Joseph G. 1993. "The Demand for and Return to Education When Education Outcomes Are Uncertain." *Journal of Labor Economics* 11 (1, Part 1):48–83.

Altonji, Joseph G, Peter Arcidiacono, and Arnaud Maurel. 2016. "The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects." In *Handbook of the Economics of Education*, vol. 5. Elsevier, 305–396.

Amiti, Mary, Stephen J Redding, and David E Weinstein. 2019. "The Impact of the 2018 Tariffs on Prices and Welfare." *Journal of Economic Perspectives* 33 (4):187–210.

Arcidiacono, Peter, V Joseph Hotz, and Songman Kang. 2012. "Modeling College Major Choices Using Elicited Measures of Expectations and Counterfactuals." *Journal of Econometrics* 166 (1):3–16.

Atkin, David. 2016. "Endogenous Skill Acquisition and Export Manufacturing in Mexico." *American Economic Review* 106 (8):2046–2085.

Autor, David, Anne Beck, David Dorn, and Gordon H Hanson. 2024. "Help for the Heartland? The Employment and Electoral Effects of the Trump Tariffs in the United States." Tech. rep., National Bureau of Economic Research.

Autor, David H and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5):1553–1597.

Bai, Yan, Keyu Jin, and Dan Lu. 2025. "Technological Rivalry and Optimal Dynamic Policy in an Open Economy." *Journal of Political Economy Macroeconomics* 3 (3):382–417.

Benguria, Felipe and Felipe Saffie. 2020. "The Impact of the 2018-2019 Trade War on US Local Labor Markets." *Available at SSRN 3542362* .

Blanchard, Emily J and William W Olney. 2017. "Globalization and Human Capital Investment: Export Composition Drives Educational Attainment." *Journal of International Economics* 106:165–183.

Blom, Erica, Brian C Cadena, and Benjamin J Keys. 2021. "Investment over the Business Cycle: Insights from College Major Choice." *Journal of Labor Economics* 39 (4):1043–1082.

Bo, Shiyu, Jing Liu, Ji-Liang Shiu, Yan Song, and Sen Zhou. 2019. "Admission Mechanisms and the Mismatch between Colleges and Students: Evidence from a Large Administrative Dataset from China." *Economics of Education Review* 68:27–37.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-Experimental Shift-Share Research Designs." *The Review of Eonomic Studies* 89 (1):181–213.

Burstein, Ariel, Javier Cravino, and Jonathan Vogel. 2013. "Importing Skill-Biased Technology." *American Economic Journal: Macroeconomics* 5 (2):32–71.

Chen, Yan and Onur Kesten. 2017. "Chinese College Admissions and School Choice Reforms: A Theoretical Analysis." *Journal of Political Economy* 125 (1):99–139.

Chor, Davin and Bingjing Li. 2024. "Illuminating the Effects of the US-China Tariff War on China's Economy." *Journal of International Economics* :103926.

Conlon, John J. 2021. "Major Malfunction: A Field Experiment Correcting Undergraduates' Beliefs about Salaries." *Journal of Human Resources* 56 (3):922–939.

Eble, Alex and Feng Hu. 2022. "Signals, Information, and the Value of College Names." *Review of Economics and Statistics* :1–45.

Fajgelbaum, Pablo, Pinelopi Goldberg, Patrick Kennedy, Amit Khandelwal, and Daria Taglioni. 2024. "The US-China Trade War and Global Reallocations." *American Economic Review: Insights* 6 (2):295–312.

Fajgelbaum, Pablo D, Pinelopi K Goldberg, Patrick J Kennedy, and Amit K Khandelwal. 2020. "The Return to Protectionism." *The Quarterly Journal of Economics* 135 (1):1–55.

Fan, Jingting. 2019. "Internal Geography, Labor Mobility, and the Distributional Impacts of Trade." *American Economic Journal: Macroeconomics* 11 (3):252–288.

Fan, Jingting and Lei Li. 2025. "Skill-Biased Imports, Skill Acquisition, and Migration." *Journal of International Economics* 157:104128.

Feng, Chaonan, Liyan Han, and Lei Li. 2023. "Who Pays for the Tariffs and Why? A Tale of Two Countries." Tech. rep., CESifo Working Paper No. 10497.

Flaaen, Aaron and Justin R Pierce. 2024. "Disentangling the Effects of the 2018-2019 Tariffs on a Globally Connected U.S. Manufacturing Sector." *The Review of Economics and Statistics* .

Gemici, Ahu and Matthew Wiswall. 2014. "Evolution of Gender Differences in Post-secondary Human Capital Investments: College Majors." *International Economic Review* 55 (1):23–56.

Goswami, Sanjana. 2020. "Employment Consequences of US Trade Wars." *University of California Irvine Working Paper* .

Greenland, Andrew and John Lopresti. 2016. "Import Exposure and Human Capital Adjustment: Evidence from the US." *Journal of International Economics* 100:50–60.

Han, Liyan, Lei Li, Ying Li, and Jingfeng Luo. 2023. "Clustering as a Shield: Mitigating the Negative Effects of the US-China Trade War." *Working Paper* .

He, Chuan, Karsten Mau, and Mingzhi Xu. 2021. "Trade Shocks and Firms Hiring Decisions: Evidence from Vacancy Postings of Chinese Firms in the Trade War." *Labour Economics* 71:102021.

Jiao, Yang, Zhikuo Liu, Zhiwei Tian, and Xiaxin Wang. 2024. "The Impacts of the US Trade War on Chinese Exporters." *Review of Economics and Statistics* 106 (6):1576–1587.

Ju, Jiandong, Hong Ma, Zi Wang, and Xiaodong Zhu. 2024. "Trade Wars and Industrial Policy Competitions: Understanding the US-China Economic Conflicts." *Journal of Monetary Economics* 141:42–58.

Khanna, Gaurav, Kevin Shih, Ariel Weinberger, Mingzhi Xu, and Miaojie Yu. 2025. "Trade liberalization and Chinese Students in US Higher Education." *Review of Economics and Statistics* 107 (5):1291–1309.

Li, Bingjing. 2018. "Export Expansion, Skill Acquisition and Industry Specialization: Evidence from China." *Journal of International Economics* 114:346–361.

Li, Hongbin, Lingsheng Meng, Kai Mu, and Shaoda Wang. 2024. "English Language Requirement and Educational Inequality: Evidence from 16 Million College Applicants in China." *Journal of Development Economics* 168:103271.

Mane, Klint, Geunyong Park, and Ande Shen. 2025. "High-Tech Clusters, Labor Demand, and Inequality: Evidence from "Made in China 2025"." *Regional Science and Urban Economics* :104142.

Parro, Fernando. 2013. "Capital-Skill Complementarity and the Skill Premium in a Quantitative Model of Trade." *American Economic Journal: Macroeconomics* 5 (2):72–117.

Pierce, Justin R and Peter K Schott. 2012. "A Concordance between Ten-Digit US Harmonized System Codes and SIC/NAICS Product Classes and Industries." *Journal of Economic and Social Measurement* 37 (1-2):61–96.

Smeets, Valerie, Lin Tian, and Sharon Traiberman. 2025. "Field Choice, Skill Specificity, and Labor Market Disruptions." Tech. rep., National Bureau of Economic Research.

Wiswall, Matthew and Basit Zafar. 2015. "Determinants of College Major Choice: Identification Using an Information Experiment." *The Review of Economic Studies* 82 (2):791–824.

Yang, Jidong, Bin Huang, Qijing Yang, and Yulong Zhou. 2022. "Impact of the US–China Trade War on Resource Allocation: Evidence from China's Land Supply." *China Economic Review* 76:101854.

Yang, Yu Alan. 2024. "On the Spatial Allocation of College Seats: Human Capital Production and the Distribution of Skilled Labor." *Available at SSRN 4745818* .

Appendix

A Data Summary

Table A1 Additional Summary Statistics

Variable	Mean	Sd	Min	Max	N
Tariff	0.007	0.006	0	0.050	925,332
Chinese Tariff	0.007	0.006	0	0.054	925,332
Standardized Admission Score	0	0.998	-6.056	4.984	925,332
enrollment number	7.907	21.991	1	1297	925,332

Notes: The tariffs are constructed as weighted average product tariffs across all Chinese trade partners, including but not limited to the U.S. (Equation 11). 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 industries	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%
Engineering Technologies	Manufacturing	25.48%
	Professional, Scientific, and Technical Services	18.17%
	Educational Services	6.63%

Continued on next page

Table A2 – continued from previous page

College major	Top three industries	Employment shares
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%
	Public Administration	14.06%
	Manufacturing	10.11%
Fine Arts	Educational Services	19.47%
	Professional, Scientific, and Technical Services	15.95%

Continued on next page

Table A2 – continued from previous page

College major	Top three industries	Employment shares
	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 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 A4 Majors with the Largest Tariff Exposure and Score Increases

Major Group	Observations	Share
Mechanical	4,801	47.92
Materials	1,493	14.9
Electronic Information	743	7.42
Instrumentation	526	5.25
Aerospace	389	3.88
Food Science and Engineering	236	2.36
Textile	233	2.33
Logistics Management and Engineering	198	1.98
Automation	198	1.98
Electricity	179	1.79
Chemical and Pharmaceutical	175	1.75
E-commerce	126	1.26
Plant Production	113	1.13
Industrial Engineering	102	1.02
Light Industry	102	1.02
Agricultural Engineering	81	0.81
Safety Science and Engineering	70	0.7
Transportation	59	0.59
Management Science and Engineering	59	0.59
Forestry Engineering	39	0.39
Mechanics	31	0.31
Nature Conservation and Environmental Ecology	17	0.17
Geology	16	0.16
Herbology	15	0.15
Surveying and Mapping	10	0.1
Environmental Science and Engineering	8	0.08

Notes: This table shows the fields which experienced the largest increases in tariff exposure during the trade war, included in the bin on the far right of Figure 6. The observations are the number of province-track-college-major enrollment admissions in this bin. The share calculates the proportion of this specific major group in total admissions.

B Tariff and Trade Data

This section details tariff and trade data collection, 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.

B.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 collect the monthly tariffs imposed by 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.[10] 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 collect the monthly retaliatory import tariffs imposed by China. 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.

Third, we collect the tariffs imposed by other countries on Chinese exporters. The HS6 product level tariffs imposed by other countries are from the United Nations Conference on Trade and Development (UNCTAD) database.

Lastly, we collect Chinese tariff imposed on other non-US trade partners. We manually collected data on country-specific HS8 product-level import tariff adjustments from the MFN

[10] 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).

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.

B.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 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.

B.3 Construction of Province-major Tariff Shocks

First, we compute the average tariff faced by each province-HS6-product pair as an export-share-weighted average across export destination countries, using province-specific 2017 destination shares as weights. Intuitively, provinces that exported a larger share of a given product to the United States before the trade war are more exposed to U.S. tariff changes on that product.

$$\tau_{pkt} = \sum_{c} \frac{Export_{pck,2017}}{Export_{pk,2017}} \times \tau_{ckt} \tag{11}$$

c, p, k, t represent the export destination country, Chinese province, HS6 product, and time, respectively. τ_{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.

Second, we aggregate province-product exposure to the province-industry level using the product-to-industry concordance in Pierce and Schott (2012) and the export share of each HS6 product within each industry.

$$\tau_{pjt} = \sum_{k \in j} \frac{\frac{1}{N_k} Export_{pk,2017}}{Export_{pj,2017}} \times \tau_{pkt} \tag{12}$$

p, j, k, t denote the province, industry, HS6 product, and time, respectively. τ_{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.[11] Then, we use the official code list of the American Community Survey to map NAICS6 industries to ACS industries to complete the second step.[12]

Third, we map industries to majors based on the industry distribution of college graduates by major. Specifically, we use American Community Survey (ACS) data to obtain major-by-industry employment shares and use these shares to convert province-industry exposure into a province-major tariff shock.

$$\tau_{pmt} = \sum_j Weight_{jm,2017} \times \tau_{pjt} \tag{13}$$

$$Weight_{jm,2017} = \frac{Employ_{jm,2017}}{\sum_j Employ_{jm,2017}} \tag{14}$$

τ_{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. The denominator $\sum_j Employ_{jm,2017}$ represents the total number of individuals with major m employed across all industries. However, the ACS data are based on the American degree classification system rather than the Chinese one. 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.

B.4 Diagnostics on the Tariff Exposure

In this subsection, we evaluate the key identifying assumption of the shift-share design following Borusyak, Hull, and Jaravel (2022). Our causality identification relies on the exogeneity of shifts, requiring tariff shocks to be as good as randomly assigned. Specifically, we first residualize the tariff-exposure and, using the end-of-2019 tariff as an illustrative benchmark, present two diagnostic scatterplots. Figure B1 residualizes tariff at detailed major level,

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

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

and Figure B2 applies an analogous residualization at the province–major level. In both cases, the residuals are centered around zero and exhibit substantial dispersion. Taken together, these patterns alleviate concerns that our estimated effects on major choice are mechanically driven by major-category differences or by a small number of influential observations.

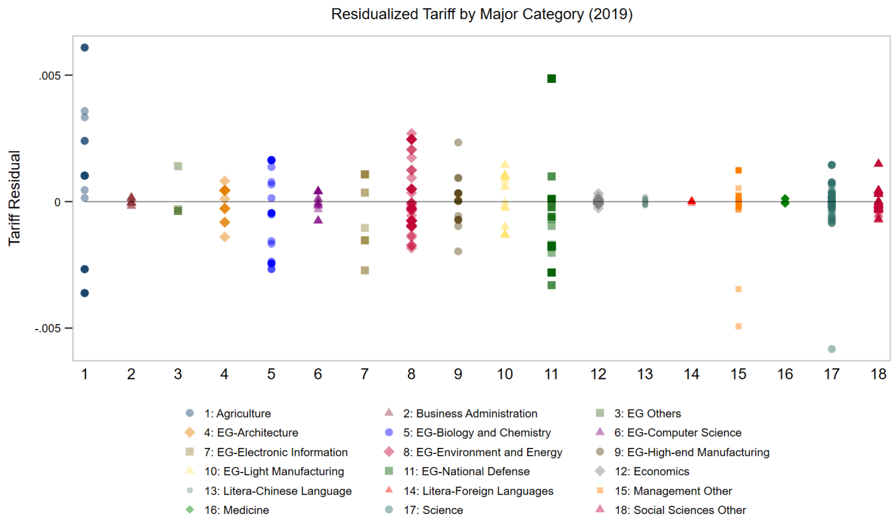

Figure B1 Residualized Tariff by Major Category (2019)

Notes: Major-level residuals are obtained by regressing major-level tariff on major category fixed effects.

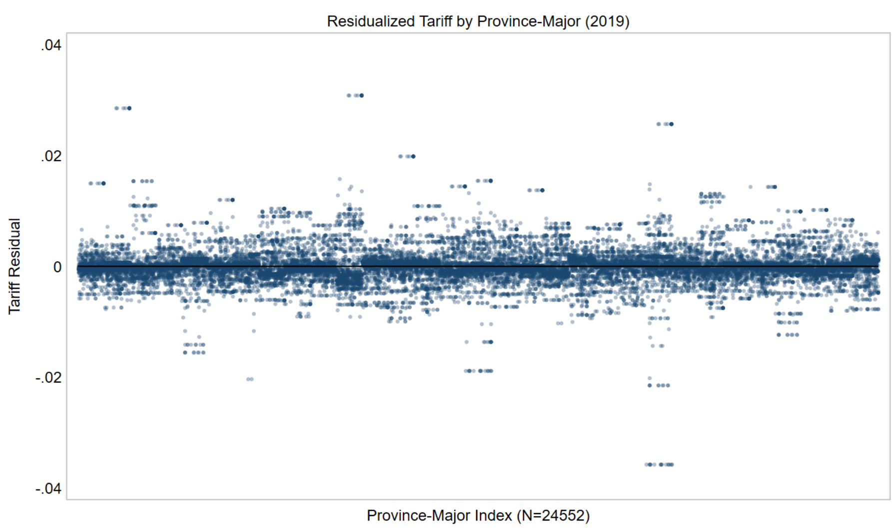

Figure B2 Residualized Tariff by Province-Major (2019)

Notes: Province–major residuals are obtained by regressing province-major tariff on province and major fixed effects.

C Job Posting Data

Using firm-level job postings from China's online recruitment platform 51*job*, we construct city–occupation–month measures of posted wages and hiring demand, and we compute province–major–year measures of the wage returns to college majors. Processing the raw postings is nontrivial, as it requires extensive data cleaning and the assignment of standardized occupational codes to each posting. This section describes the full process and key implementation details.

C.1 Cleaning and Processing of the Raw Data

Our data are collected from 51*job*, an online recruitment platform founded in 1999 that hosts vacancy postings across a broad range of industries and is particularly strong in campus recruitment services and white-collar positions. The platform serves a diverse set of employers, including state-owned enterprises, foreign-invested firms, publicly listed companies, and small and medium-sized enterprises; as of 2025, it reports a cumulative user base of more than 200 million. Using web-scraping techniques, we compile posting-level daily job-advertisement records from 51*job* over 2017–2020, yielding approximately 300 million raw observations. Each record contains the job title, job description, posted wage, stated hiring demand (number of vacancies/recruits), education and major requirements, and firm information.

We begin by implementing the following steps on the raw postings. (1) We drop duplicate job postings that the same firm releases multiple times within a given day or month. Firms may repost identical vacancies to increase visibility before the position is filled, which would mechanically inflate measured hiring demand. (2) We exclude postings with missing wage information. We then standardize several key variables as follows.

Posted wages. We convert all wage data to a monthly basis. Wages are reported as hourly, daily, weekly, monthly, or annual pay, with monthly pay being the most common. We standardize hourly, daily, and weekly wages using 8 hours per day, 5 days per week, and 4.3 weeks per month (i.e., hourly pay is multiplied by $8 \times 5 \times 4.3$, daily pay by 5×4.3, and weekly pay by 4.3). Annual pay is divided by 12.

Education requirement. Following census conventions, we map education requirements into eight categories—primary school, junior middle school, senior high school, secondary vocational school, junior college, bachelor's degree, master's degree, and PhD—and we retain postings that require a bachelor's degree or above.

Major requirement. Using the textual information in postings, we crosswalk stated major requirements to the Ministry of Education's Catalogue of Undergraduate Majors for Regular

Higher Education Institutions and extract the corresponding six-digit major code(s). When a posting lists n eligible majors (e.g., "Computer Science, Mathematics, or Statistics" for a data analyst position in Figure C1), we split the posting into n records, assigning each record one major code. The vacancy count is apportioned equally (set to $1/n$ of the original), while all other variables are held fixed.

City codes. We map the location information in each posting to China's 2022 administrative division codebook (county level and above) to obtain the corresponding six-digit administrative code.

Figure C1 Example Job Posting on 51*job*

Notes: This figure provides a screenshot of a job posting on the online recruitment platform 51*job*, including the job title, job description, posted wage, education and major requirements, and employer information.

C.2 Assigning Standard Occupational Classification Codes to Job Postings

Job titles in the raw postings are defined by firms and do not follow a standardized categorization. To implement our empirical analysis, we need to assign each posting to a standardized occupation. Using the textual job description in each posting, we employ a large language model (Claude-3-Opus) to map postings to six-digit occupations in the 2018 Standard Occupational Classification (SOC). This procedure yields 220 distinct six-digit SOC occupations in our data, which span 22 two-digit SOC major groups.[13] All detailed occupations included in our sample are reported in Table C1. The workflow is as follows:

(1) We compile all unique job titles and associated occupation descriptions, and retain the 500,000 most common titles (ranked by stated hiring demand) to construct a mapping

[13]There are 23 major groups in SOC; Our sample contains no observations in major group 55——Military Specific Occupations.

dictionary from job titles to SOC codes.

(2) We input each title together with its duty description into the LLM, and prompt it to assign the corresponding six-digit SOC code based on the 2018 SOC (occupation titles and six-digit codes).

(3) We validate whether the returned code exists in the 2018 SOC. In some cases, the model outputs a code from a different SOC revision or a non-existent code. Valid codes are recorded in the dictionary; invalid outputs are stored in an error set.

(4) For records in the error set, we provide the LLM with the job title, duty description, and the 2018 SOC documentation, and ask it to identify the most appropriate SOC occupation and return the corresponding code. We again validate the returned code against the 2018 SOC. If the code remains invalid after the second attempt, we drop the record from further mapping.

(5) Using the title-to-SOC dictionary constructed from the top 500,000 titles, we classify the remaining postings via dictionary-based string matching, extracting the SOC code when a posting's raw job title contains a title/keyword entry in the dictionary.

Table C1 SOC-2digit Occupation Groups and Detailed Occupations

SOC	Occupation Group	Detailed occupation
11	Management Occupations	11-1021 General and Operations Managers;11-2011 Advertising and Promotions Managers; 11-3021 Computer and Information Systems Managers;11-3031 Financial Managers;11-3051 Industrial Production Managers;11-3061 Purchasing Managers;11-3071 Transportation, Storage, and Distribution Managers;11-3111 Compensation and Benefits Managers;11-3121 Human Resources Managers;11-3131 Training and Development Managers;11-9013 Farmers, Ranchers, and Other Agricultural Managers;11-9021 Construction Managers;11-9041 Architectural and Engineering Managers;11-9051 Food Service Managers;11-9081 Lodging Managers;11-9111 Medical and Health Services Managers;11-9121 Natural Sciences Managers;11-9141 Property, Real Estate, and Community Association Managers;11-9151 Social and Community Service Managers; 11-9161 Emergency Management Directors.
13	Business and Financial Operations Occupations	13-1011 Agents and Business Managers of Artists, Performers, and Athletes;13-1021 Buyers and Purchasing Agents, Farm Products;13-1022 Wholesale and Retail Buyers, Except Farm Products; 13-1023 Purchasing Agents, Except Wholesale, Retail, and Farm Products;13-1041 Compliance Officers;13-1051 Cost Estimators;13-1081 Logisticians;13-1111 Management Analysts;13-1121 Meeting, Convention, and Event Planners;13-1131 Fundraisers;13-1141 Compensation, Benefits, and Job Analysis Specialists;13-1151 Training and Development Specialists;13-1161 Market Research Analysts and Marketing Specialists;13-1199 Business Operations Specialists, All Other; 13-2011 Accountants and Auditors;13-2031 Budget Analysts;13-2041 Credit Analysts;13-2051 Financial and Investment Analysts;13-2052 Personal Financial Advisors;13-2053 Insurance Underwriters;13-2082 Tax Preparers;13-2099 Financial Specialists, All Other.
15	Computer and Mathematical Occupations	15-2031 Operations Research Analysts.
17	Architecture and Engineering Occupations	17-2011 Aerospace Engineers;17-2041 Chemical Engineers;17-2051 Civil Engineers;17-2061 Computer Hardware Engineers;17-2081 Environmental Engineers;17-2121 Marine Engineers and Naval Architects;17-2131 Materials Engineers;17-2141 Mechanical Engineers;17-3031 Surveying and Mapping Technicians.
19	Life, Physical, and Social Science Occupations	19-2021 Atmospheric and Space Scientists;19-3011 Economists;19-3051 Urban and Regional Planners;19-4021 Biological Technicians;19-4031 Chemical Technicians.
21	Community and Social Service Occupations	21-1093 Social and Human Service Assistants;21-2011 Clergy.
23	Legal Occupations	23-2011 Paralegals and Legal Assistants.
25	Educational Instruction and Library Occupations	25-4031 Library Technicians.

SOC	Occupation Group	Detailed occupation
27	Arts, Design, Entertainment, Sports, and Media Occupations	27-2011 Actors;27-2012 Producers and Directors;27-3031 Public Relations Specialists;27-3041 Editors;27-3042 Technical Writers;27-3043 Writers and Authors;27-4021 Photographers.
29	Healthcare Practitioners and Technical Occupations	29-1031 Dietitians and Nutritionists;29-1051 Pharmacists;29-1123 Physical Therapists;29-1126 Respiratory Therapists;29-1131 Veterinarians;29-1141 Registered Nurses;29-2061 Licensed Practical and Licensed Vocational Nurses;29-2081 Opticians, Dispensing.
31	Healthcare Support Occupations	31-9094 Medical Transcriptionists;31-9097 Phlebotomists.
33	Protective Service Occupations	33-1012 First-Line Supervisors of Police and Detectives;33-1021 First-Line Supervisors of Firefighting and Prevention Workers;33-1099 First-Line Supervisors of Protective Service Workers, All Other;33-2011 Firefighters;33-3021 Detectives and Criminal Investigators;33-9021 Private Detectives and Investigators.
35	Food Preparation and Serving Related Occupations	35-1011 Chefs and Head Cooks;35-1012 First-Line Supervisors of Food Preparation and Serving Workers;35-2021 Food Preparation Workers;35-3011 Bartenders;35-3031 Waiters and Waitresses; 35-3041 Food Servers, Nonrestaurant;35-9031 Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop.
37	Building and Grounds Cleaning and Maintenance Occupations	37-1011 First-Line Supervisors of Housekeeping and Janitorial Workers;37-1012 First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers;37-2012 Maids and Housekeeping Cleaners;37-2021 Pest Control Workers.
39	Personal Care and Service Occupations	39-2011 Animal Trainers;39-2021 Animal Caretakers;39-3031 Ushers, Lobby Attendants, and Ticket Takers;39-9011 Childcare Workers;39-9041 Residential Advisors;39-9099 Personal Care and Service Workers, All Other.
41	Sales and Related Occupations	41-1011 First-Line Supervisors of Retail Sales Workers;41-1012 First-Line Supervisors of Non-Retail Sales Workers;41-2021 Counter and Rental Clerks;41-2022 Parts Salespersons;41-2031 Retail Salespersons;41-3011 Advertising Sales Agents;41-3021 Insurance Sales Agents;41-3031 Securities, Commodities, and Financial Services Sales Agents;41-9031 Sales Engineers;41-9041 Telemarketers;41-9091 Door-to-Door Sales Workers, News and Street Vendors, and Related Workers;41-9099 Sales and Related Workers, All Other.
43	Office and Administrative Support Occupations	43-1011 First-Line Supervisors of Office and Administrative Support Workers;43-2011 Switchboard Operators, Including Answering Service;43-2021 Telephone Operators;43-3011 Bill and Account Collectors;43-3021 Billing and Posting Clerks;43-3031 Bookkeeping, Accounting, and Auditing Clerks;43-3051 Payroll and Timekeeping Clerks;43-3061 Procurement Clerks;43-3099 Financial Clerks, All Other;43-4011 Brokerage Clerks;43-4031 Court, Municipal, and License Clerks;43-4041 Credit Authorizers, Checkers, and Clerks;43-4051 Customer Service Representatives;43-4071 File Clerks;43-4111 Interviewers, Except Eligibility and Loan;43-4161 Human Resources Assistants, Except Payroll and Timekeeping;43-4171 Receptionists and Information Clerks;43-4181 Reservation and Transportation Ticket Agents and Travel Clerks; 43-4199 Information and Record Clerks, All Other;43-5011 Cargo and Freight Agents;43-5021 Couriers and Messengers;43-5061 Production, Planning, and Expediting Clerks;43-5071 Shipping, Receiving, and Inventory Clerks;43-5111 Weighers, Measurers, Checkers, and Samplers, Recordkeeping;43-9021 Data Entry Keyers;43-9022 Word Processors and Typists;43-9041 Insurance Claims and Policy Processing Clerks;43-9051 Mail Clerks and Mail Machine Operators, Except Postal Service;43-9061 Office Clerks, General;43-9071 Office Machine Operators, Except Computer;43-9081 Proofreaders and Copy Markers;43-9111 Statistical Assistants.
45	Farming, Fishing, and Forestry Occupations	45-2011 Agricultural Inspectors;45-2041 Graders and Sorters, Agricultural Products.
47	Construction and Extraction Occupations	47-1011 First-Line Supervisors of Construction Trades and Extraction Workers;47-2031 Carpenters;47-2061 Construction Laborers;47-2111 Electricians;47-2121 Glaziers;47-2211 Sheet Metal Workers;47-2221 Structural Iron and Steel Workers;47-4021 Elevator and Escalator Installers and Repairers;47-4041 Hazardous Materials Removal Workers.
49	Installation, Maintenance, and Repair Occupations	49-1011 First-Line Supervisors of Mechanics, Installers, and Repairers;49-2011 Computer, Automated Teller, and Office Machine Repairers;49-2092 Electric Motor, Power Tool, and Related Repairers;49-2096 Electronic Equipment Installers and Repairers, Motor Vehicles;49-2097 Audiovisual Equipment Installers and Repairers;49-3011 Aircraft Mechanics and Service Technicians;49-3021 Automotive Body and Related Repairers;49-3022 Automotive Glass Installers and Repairers;49-3023 Automotive Service Technicians and Mechanics;49-3031 Bus and Truck Mechanics and Diesel Engine Specialists;49-9021 Heating, Air Conditioning, and Refrigeration Mechanics and Installers;49-9043 Maintenance Workers, Machinery;49-9044 Millwrights;49-9051 Electrical Power-Line Installers and Repairers;49-9071 Maintenance and Repair Workers, General; 49-9096 Riggers;49-9098 Helpers–Installation, Maintenance, and Repair Workers.

SOC	Occupation Group	Detailed occupation
51	Production Occupations	51-1011 First-Line Supervisors of Production and Operating Workers;51-2011 Aircraft Structure, Surfaces, Rigging, and Systems Assemblers;51-2031 Engine and Other Machine Assemblers; 51-2041 Structural Metal Fabricators and Fitters;51-3011 Bakers;51-3091 Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders;51-3092 Food Batchmakers;51-3099 Food Processing Workers, All Other;51-4021 Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic;51-4022 Forging Machine Setters, Operators, and Tenders, Metal and Plastic;51-4023 Rolling Machine Setters, Operators, and Tenders, Metal and Plastic;51-4041 Machinists;51-4111 Tool and Die Makers;51-5111 Prepress Technicians and Workers;51-5112 Printing Press Operators;51-5113 Print Binding and Finishing Workers;51-6011 Laundry and Dry-Cleaning Workers;51-6021 Pressers, Textile, Garment, and Related Materials;51-6031 Sewing Machine Operators;51-6063 Textile Knitting and Weaving Machine Setters, Operators, and Tenders;51-6064 Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders;51-6093 Upholsterers;51-7041 Sawing Machine Setters, Operators, and Tenders, Wood; 51-7042 Woodworking Machine Setters, Operators, and Tenders, Except Sawing;51-8021 Stationary Engineers and Boiler Operators;51-8031 Water and Wastewater Treatment Plant and System Operators;51-9041 Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders;51-9051 Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders; 51-9061 Inspectors, Testers, Sorters, Samplers, and Weighers;51-9071 Jewelers and Precious Stone and Metal Workers;51-9111 Packaging and Filling Machine Operators and Tenders;51-9151 Photographic Process Workers and Processing Machine Operators;51-9194 Etchers and Engravers; 51-9195 Molders, Shapers, and Casters, Except Metal and Plastic;51-9196 Paper Goods Machine Setters, Operators, and Tenders;51-9197 Tire Builders;51-9198 Helpers–Production Workers.
53	Transportation and Material Moving Occupations	53-3099 Motor Vehicle Operators, All Other;53-4031 Railroad Conductors and Yardmasters; 53-6031 Automotive and Watercraft Service Attendants;53-7021 Crane and Tower Operators; 53-7051 Industrial Truck and Tractor Operators;53-7061 Cleaners of Vehicles and Equipment; 53-7062 Laborers and Freight, Stock, and Material Movers, Hand;53-7063 Machine Feeders and Offbearers;53-7064 Packers and Packagers, Hand;53-7081 Refuse and Recyclable Material Collectors.

D Enrollment Quotas

To investigate the impact on enrollment quota, 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 D1 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.

Table D1 Tariff and Enrollment

	Ln(Enrollment Quota)			Enrollment Quota Share		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Majors	Drop New Majors	By College Type	All Majors	Drop New Majors	By College Type
Tariff	3.135***	3.487***	0.661	0.162***	0.176***	0.047
	(1.021)	(1.019)	(1.074)	(0.045)	(0.044)	(0.055)
Tariff × National Elite			6.669***			0.365***
			(1.264)			(0.062)
Tariff × Local Elite			3.914***			0.141***
			(0.892)			(0.045)
Controls	Y	Y	Y	Y	Y	Y
Prov-College-Track-Major Cat FE	Y	Y	Y	Y	Y	Y
Prov-Track-Year FE	Y	Y	Y	Y	Y	Y
Prov-Major Cat-Year FE	Y	Y	Y	Y	Y	Y
Prov-College-Batch-Year FE	Y	Y	Y	Y	Y	Y
Observations	953,703	951,543	951,543	953,703	951,543	951,543
R-squared	0.851	0.851	0.851	0.861	0.861	0.861

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-batch-major-year level. We control for province-college-track-major category, province-track-year, province-major category-year, and province-college-batch-year fixed effects in all columns. Major category level fixed effect refers to 2-digit major. The province-major-year level Chinese tariff on foreign imports and its interactions with elite university dummies are included as control variables in all columns. This table reports standard errors clustered at the province-major level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 if we interpret the baseline results as purely the rise in student interest in STEM fields, then it is underestimated if the enrollment quota were not controlled for. We also run a set of regression by controlling for the enrollment quotas directly and our main conclusions are not changed. We decide not to show the results here because it suffers from the bad control problem. The results are available upon request.

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.

E Robustness Checks

E.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 E1 show minimal change in the regression coefficient after excluding these regions.

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 (2), 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 (3) show that the core conclusions remain unchanged.

E.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 E2, we exclude teacher training majors and found the core conclusions were unaffected. A separate regression in column (2) confirms that tariffs also had 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 E1 Excluding Special Student Group

Admission Score	(1) Non-Minority	(2) Minority province	(3) Drop oriented student	(4) Drop special talent student
Tariff	1.621**	4.930***	1.836***	1.840***
	(0.653)	(1.727)	(0.624)	(0.621)
Controls	Y	Y	Y	Y
Prov-College-Track-Major Cat FE	Y	Y	Y	Y
Prov-Track-Year FE	Y	Y	Y	Y
Prov-Major Cat-Year FE	Y	Y	Y	Y
Prov-College-Batch-Year FE	Y	Y	Y	Y
Observations	815,600	109,732	924,204	924,649
R-squared	0.969	0.971	0.969	0.969

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 province-college-track-batch-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-college-track-major category, province-track-year, province-major category-year, and province-college-batch-year fixed effects in all columns. The province-major-year level average Chinese tariff on foreign imports is included as control variables in all columns. Major category level fixed effect refers to 2-digit major. Standard errors are clustered at the province-major level. *** p < 0.01, ** p < 0.05, * p < 0.1.

E.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 E3 indicate that our findings remain robust. According to column (3), a one 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 × 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 × 0.28% = 1,195.18 positions in the admissions ranking.

Table E2 Excluding Special Major Groups

Admission Score	(1) Non-teacher Major	(2) Teacher Major	(3) Drop Sino-foreign Program	(4) Drop New Majors
Tariff	1.683***	2.981	1.790***	2.279***
	(0.629)	(3.655)	(0.625)	(0.573)
Controls	Y	Y	Y	Y
Prov-College-Track-Major Cat FE	Y	Y	Y	Y
Prov-Track-Year FE	Y	Y	Y	Y
Prov-Major Cat-Year FE	Y	Y	Y	Y
Prov-College-Batch-Year FE	Y	Y	Y	Y
Observations	878,558	37,611	923,194	907,223
R-squared	0.970	0.970	0.969	0.973

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 province-college-track-batch-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-college-track-major category, province-track-year, province-major category-year, and province-college-batch-year fixed effects in all columns. Major category level fixed effect refers to 2-digit major. The province-major-year level Chinese tariff on foreign imports is included as control variables in all columns. Standard errors are clustered at the province-major level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E.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 E4, indicate that the U.S. punitive tariffs significantly raised the admission scores for affected majors, consistent with our previous findings.

E.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 specific major m,

Table E3 Alternative Measures of the Dependent Variable

	(1) Standardized Admission Score	(2) Ln(Admission score)	(3) Score Percentile
Tariff	1.820***	0.211***	0.297**
	(0.624)	(0.080)	(0.124)
Controls	Y	Y	Y
Prov-College-Track-Major Cat FE	Y	Y	Y
Prov-Track-Year FE	Y	Y	Y
Prov-Major Cat-Year FE	Y	Y	Y
Prov-College-Batch-Year FE	Y	Y	Y
Observations	925,332	925,332	924,620
R-squared	0.969	0.984	0.973

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-batch-major-year level. We control for province-college-track-major category, province-track-year, province-major category-year, and province-college-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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 E5 show that the coefficient on tariffs is still significantly positive, but the magnitude is reduced compared to in Table 2.

E.6 College-Specific Shocks: College 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. 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 E6 show that our key conclusions remain unaffected.

Table E4 Using Only U.S. Punitive and Chinese Retaliatory Tariffs

	Standardized Admission Score			
Variables	(1)	(2)	(3)	(4)
Tariff	1.253***	1.192***	0.934***	0.719***
	(0.207)	(0.221)	(0.202)	(0.228)
Tariff×Nation Elite College		0.402*		0.861***
		(0.240)		(0.262)
Tariff×Local Elite College			0.831***	1.044***
			(0.253)	(0.274)
Controls	Y	Y	Y	Y
Prov-College-Track-Major Cat FE	Y	Y	Y	Y
Prov-Track-Year FE	Y	Y	Y	Y
Prov-Major Cat-Year FE	Y	Y	Y	Y
Prov-College-Batch-Year FE	Y	Y	Y	Y
Observations	925,332	925,332	925,332	925,332
R-squared	0.969	0.969	0.969	0.969

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-batch-major-year level. We control for province-college-track-major category, province-track-year, province-major category-year, and province-college-batch-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 province-major level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E5 Using Only National Export Structure in Constructing Tariff Exposure

	Standardized Admission Score			
Variables	(1)	(2)	(3)	(4)
Tariff	0.874	0.570	0.165	-0.571
	(1.962)	(1.939)	(1.824)	(1.757)
Tariff×Nation Elite College		1.994*		3.110**
		(1.089)		(1.280)
Tariff×Local Elite College			1.925**	2.638**
			(0.974)	(1.096)
Controls	Y	Y	Y	Y
Prov-College-Track-Major Cat FE	Y	Y	Y	Y
Prov-Track-Year FE	Y	Y	Y	Y
Prov-Major Cat-Year FE	Y	Y	Y	Y
Prov-College-Batch-Year FE	Y	Y	Y	Y
Observations	925,332	925,332	925,332	925,332
R-squared	0.969	0.969	0.969	0.969

Notes: This table reports estimates of the effect of the tariff shock on admission scores. The dependent variable is standardized admission scores at the province-college-track-batch-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-batch-major-year level. We control for province-college-track-major category, province-track-year, province-major category-year, and province-college-batch-year fixed effects in all columns. 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 major level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E.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 E6 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.

E.8 Study Abroad

Chinese high-school graduates choose among domestic university, overseas study, and employment. Holding other factors constant, an increase in the contemporaneous share of students studying abroad will ease competition among domestic university and may lower admission score. Khanna et al. (2025) find that trade liberalization significantly increases

Table E6 Other Robustness Checks

Admiassion Score	(1) Drop Upgrading Colleges	(2) Drop Renamed Colleges	(3) Add City-level Tariff
Tariff	1.802***	1.625***	1.861***
	(0.626)	(0.590)	(0.627)
College Location Tariff			0.863***
			(0.276)
Controls	Y	Y	Y
Prov-College-Track-Major Cat FE	Y	Y	Y
Prov-Track-Year FE	Y	Y	Y
Prov-Major Cat-Year FE	Y	Y	Y
Prov-College-Batch FE	N	N	Y
Prov-College-Batch-Year FE	Y	Y	N
Observations	918,541	922,342	923,451
R-squared	0.969	0.969	0.964

Notes: This table reports the results of other robustness checks. The dependent variable is standardized admission scores at the province-college-track-batch-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-batch-major-year level. We control for province-track-year, province-major category-year, and province-college-track-major fixed effects in all columns. Column (1)-(2) include college-province-batch-year fixed effects and Column (3) includes college-province-batch-year fixed effects. Major category level fixed effect refers to 2-digit major. 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 province-major level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the number of Chinese students studying in the United States. Therefore, one concern is that fluctuations in study-abroad flows during the U.S.–China trade conflict may confound domestic major choice.

To gauge the magnitude, we compile (i) the number of Chinese students in the U.S. from the IIE (the Institute of International Education, IIE) Open Doors report and (ii) the total number of Chinese students studying abroad and the number of Gaokao registrants from China's education authorities (see Table E7). Overall, the proportion of students choosing to study in overseas colleges is small. Therefore, it should not significantly affect our results. Over 2017–2020, China sent on average 0.61 million students abroad annually, versus 10.04 million NCEE candidates, implying a global study-abroad share below 7%. The stock of Chinese students in the U.S. was about 0.349 million, suggesting a U.S. study-abroad share below 4%. Note that this is an upper-bound estimate, The Open Doors report publishes the stock rather than annual inflow, and it counts undergraduates as well as master's and doctoral students. Consequently, using these figures to approximate the share of Chinese high-school graduates who study in the United States overstates the true ratio.

Table E7 Study-Abroad Flows and NCEE Registrations in China, 2017–2020

Year	NCEE Registrants (flow, millions)	Total Studying Abroad (flow, millions)	Share Studying Abroad (Global)	Studying in the U.S. (stock, millions)	Share Studying Abroad (U.S.)
2017	9.40	0.61	6.47%	0.36	3.86%
2018	9.75	0.66	6.79%	0.37	3.79%
2019	10.31	0.70	6.82%	0.37	3.61%
2020	10.71	0.45	4.21%	0.29	2.71%

Notes: This table reports, for 2017–2020, the annual numbers of Chinese students registering for the NCEE and studying abroad. Column (2) shows the number of NCEE registrants in that year; Column (3) reports the worldwide number of Chinese students who went abroad that year (global flow, including the United States); Column (4) is the ratio of the annual study-abroad flow to NCEE registrants; Column (5) reports the number of Chinese students in the United States in that year (stock); Column (6) is the ratio of the U.S. stock of Chinese students to NCEE registrants. *Source:* NCEE registrants and total Chinese study-abroad flows are from the Ministry of Education of China. The number of Chinese students in the United States is from the Institute of International Education (IIE), Open Doors report, https://opendoorsdata.org/fact_sheets/student-mobility/.

E.9 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 result is presented in Appendix Table E8. 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 E8 Lagged Effects of Tariffs on Log Job Postings and Log Wages

Panel A: Effects on Log Job Posings

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 × 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

Panel B: Effects 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 × 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 tariffs on job postings (Panel A) and Wages (Panel B) 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 variables are the city-occupation level number of job postings and wages. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

F Variable Construction: Tariff Exposure at the City-occupation Level

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

$$\tau_{pkt} = \sum_{c} \frac{Export_{pck,2016}}{Export_{pk,2016}} \times \tau_{pckt} \tag{15}$$

$$\tau_{pjt} = \sum_{\mathrm{k \in j}} \frac{\frac{1}{\mathrm{N_k}} Export_{pk,2016}}{Export_{pj,2016}} \times \tau_{pkt} \tag{16}$$

$$\tau_{pit} = \sum_{j} Weight_{ij,2017} \times \tau_{pjt} \tag{17}$$

$$Weight_{ij,2017} = \frac{Employ_{ij,2017}}{\sum_j Employ_{ij,2017}} \tag{18}$$

τ_{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.

G Variable Construction: Technology-Exposure Measures

We construct major-level AI exposure based job-posting data from 51job.com, one of the largest Chinese online recruitment platform. Each posting contains standardized information—job title, number of openings, wage, education and experience requirements, language and computer skills, work location, posting date, and firms' information—together with a detailed description of core tasks. We draw a random sample of 613,381 postings from 2017–2020, covering 31 provinces and 392 cities, to build the AI-exposure measures.

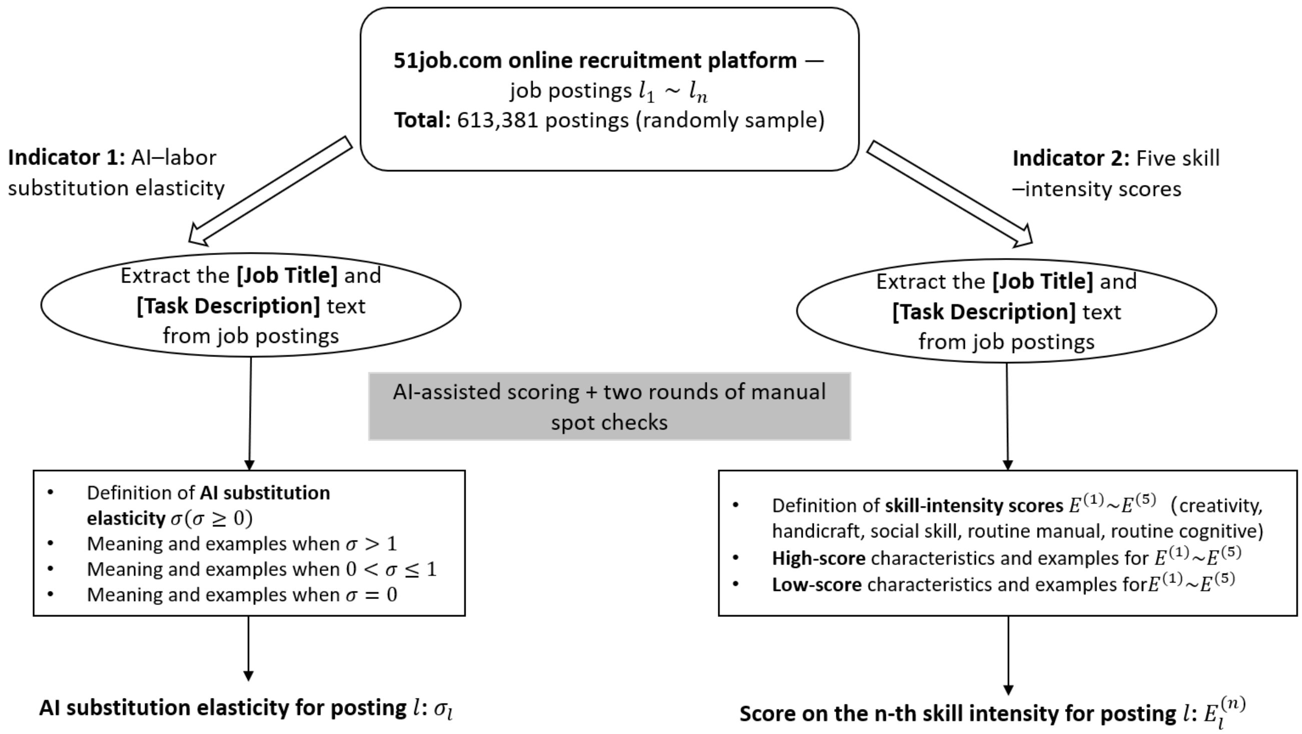

Figure G1 Building AI-Exposure Measures for Each Vacancy Posting

Notes: The figure documents how to construct posting-level technology exposure. We extract the Job Title and Task Description text from each posting and score them using an AI-assisted pipeline built on the DeepSeek API (https://api.deepseek.com). The AI–labor substitution elasticity measures firms' propensity to replace labor with AI when relative input prices move. Five-dimension skill score including creativity, handicraft, social skill, routine cognitive, and routine manual, are normalized to the [0,1] scale. Definitions, examples, and characteristics for both measures are reported in Table G1. The full scoring prompt will be released upon publication.

For each posting l, we infer: (i) AI substitution elasticity — higher values indicate greater substitutability between labor and computer capital ($\sigma > 1$: highly substitutable; $0 < \sigma < 1$: limited substitutability; $\sigma = 0$: complementarity); and (ii) five-dimension skill scores $E_l^{(n)} \in [0, 1]$ for n=1,. . . ,5: creativity, handicraft, social skill, routine manual, routine cognitive. Higher values denote greater intensity of the corresponding skill.

Table G1 Definition and Description of AI Exposure

Indicator	Definition	Description	Typical examples
		Part I. Economic Substitution Indicator	
AI–labor substitution elasticity	Measures how willing firms are to adjust the input mix between human labor and computer (AI) capital when their relative costs change. It captures the ease and propensity of replacing labor with computer technologies.	$\sigma > 1$ (high substitutability): labor and computer capital are readily interchangeable. Jobs are typically structured, repetitive, rule-based.	data-entry clerks; assembly-line workers; FAQ-type customer service; warehouse pickers.
		$0 < \sigma < 1$ (weak substitutability / strong complementarity): hard to substitute; firms tend to combine human effort with technology. Non-routine judgment.	teachers; counselors/therapists; research scientists; artists; senior managers; master technicians.
		$\sigma = 0$ (perfect complementarity): inputs must be used together.	pilot and aircraft.
		Part II. Occupational Skill Indicators	
Creativity	Ability to analyze complex information, think creatively to solve unstructured problems, and generate novel ideas or products (intellectual innovation rather than artistic talent).	**High score**: exploring new domains; designing new products/models; complex diagnosis and judgment.	High-score examples: data scientist; integrated circuit (IC) engineer (R&D); product planner; quantitative analyst; neurologist.
		Low score: highly proceduralized work requiring little original thinking.	Low-score examples: form-filling clerk; assembly-line operator.
Handicraft	Ability to perform fine hand operations, maintain bodily coordination, and execute non-standardized physical tasks that require experience and skill.	**High score**: precise, dexterous surgical/operative skills; outcomes depend on bodily precision and control.	High-score examples: surgeon; dentist; nurse; cosmetologist; hair stylist; senior repair technician.
		Low score: work is almost entirely cognitive or consists of simple manual labor.	Low-score examples: financial analyst; writer; call-center operator.
Social skill	Ability to understand, empathize, persuade, coordinate, lead, and teach others—centered on managing complex interpersonal dynamics and emotional interactions.	**High score**: intensive emotional communication; counseling; motivating teams; developing others.	High-score examples: counselor/therapist; K–12 teacher; physician (patient-facing); senior manager.
		Low score: mainly interacting with data/code/machines; minimal interpersonal demands.	Low-score examples: mathematician; some technical R&D roles (e.g., IC engineer).
Routine Manual	Degree to which work consists of programmatic, repetitive physical actions.	**High score**: operating fixed-process machinery; conveyor-belt work; standardized handling/cleaning/packaging.	High-score examples: assembly-line worker; packer; parcel sorter.
		Low score: non-routine physical tasks with high variation.	Low-score examples: dancer (physical but non-routine); CEO.

Table G1 Definition and Description of AI Exposure (continued)

Indicator	Definition	Description	Typical examples
Routine Cognitive	Degree to which work consists of structured, rule-based, repetitive cognitive tasks.	**High score**: processing formatted information (e.g., form filling, document sorting/filing, data entry) and executing standardized procedures.	High-score examples: data-entry clerk; administrative assistant; bank teller (routine transactions).
		Low score: work is uncertain and non-routine, requiring continuous problem solving and novel reasoning.	Low-score examples: strategy consultant; research scientist.

We compute province–major-level AI exposure by aggregating in one step across all cities in province p and all postings requiring major m in year t:

$$\sigma_{pmt} = \sum_{l \in \mathcal{L}_{pmt}} \omega_{l|pmt}\, \sigma_l, \tag{19}$$

$$E^{(n)}_{pmt} = \sum_{l \in \mathcal{L}_{pmt}} \omega_{l|pmt}\, E^{(n)}_l, \tag{20}$$

$$\omega_{l|pmt} = \frac{N_l}{\sum_{l \in \mathcal{L}_{pmt}} N_l}. \tag{21}$$

Here, $\mathcal{L}_{pmt}$ denotes the set of postings in province p and year t that require major m. $\omega_{l|pmt}$ is the weight for posting l within $\mathcal{L}_{pmt}$, equal to the number of openings in that posting, N_l divided by the total number of openings across all postings in $\mathcal{L}_{pmt}$.

In the mechanism analysis, we include city–major AI exposure as a control. Its construction mirrors Equations (17)–(19), with the province dimension replaced by the city dimension. As an alternative measure, we also build city–occupation (SOC 6-digit) AI exposure, computed as follows:

$$\sigma_{ikt} = \sum_{l \in \mathcal{L}_{ikt}} \omega_{l|ikt}\, \sigma_l, \tag{22}$$

$$E^{(n)}_{ikt} = \sum_{l \in \mathcal{L}_{ikt}} \omega_{l|ikt}\, E^{(n)}_l, \tag{23}$$

$$\omega_{l|ikt} = \frac{N_l}{\sum_{l \in \mathcal{L}_{ikt}} N_l}. \tag{24}$$

Here, σ_{ikt} and $E^{(n)}_{ikt}$ refer, respectively, to the AI-labor substitution elasticity and the skill-intensity score for occupation k in city i and year t. $\mathcal{L}_{ikt}$ denotes the set of job postings for occupation k in the city i and year $t.\omega_{l|ikt}$ is the weight for posting l within $\mathcal{L}_{ikt}$.

H Additional Figure

Figure H1 Screenshot from Zhang Xuefeng: "Follow Trump" in choosing college majors

Notes: This figure is taken from Xiaohongshu (RED), a popular Chinese social media platform. The image shows a screenshot from a livestream by Zhang Xuefeng, one of China's best-known gaokao counseling influencers. The headline at the top reads: "Which majors will be popular in the future? Follow Trump!"