The Ripple Effects of China's College Expansion on American Universities*

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October 14, 2025

Abstract

China's unprecedented expansion of higher education in 1999, increased annual college enrollment from 1 million to 9.6 million by 2020. We trace the global ripple effects of that expansion by examining its impact on US graduate education and local economies surrounding college towns. Combining administrative data from China's college admissions system and US visa data, we leverage the centralized quota system governing Chinese college admissions for identification and present three key findings. First, the expansion of Chinese undergraduate education drove graduate student flows to the US: every additional 100 college graduates in China led to 3.6 Chinese graduate students in the US. Second, Chinese master's students generated positive spillovers, driving the birth of new master's programs, and increasing the number of other international and American master's students, particularly in STEM fields. And third, the influx of international students supported local economies around college towns, raising job creation rates outside the universities, as well. Our findings highlight how domestic education policy in one country can reshape the academic and economic landscape of another through student migration and its broader spillovers.

Keywords: College Expansion, Foreign Students, US Universities, STEM, College Towns
JEL Codes: J61, I23, J24, F22, O15, O38

*For helpful comments, we thank Catalina Amuedo-Dorantes, Julie Cullen, Gordon Dahl, Zhiguo He, Giovanni Peri, Daniel Xu and seminar/conference participants at Young Scholars Conference (Fudan-UC Center), WEAI, Stanford SITE, and UCSD. All potential errors are our own.

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1 Introduction

In the early 2000s, China undertook one of the most dramatic higher education expansions in modern history. Between 1999 and 2010, the number of universities and colleges doubled, and college enrollment surged eightfold from around 1 million students in 1998 to over 8 million by 2018. While this expansion was designed to serve domestic development goals, its consequences likely reverberated beyond China's borders, in an era of global academic mobility. In principle, a rapid increase in college graduates in a major sending country like China could reshape graduate education in destinations such as the United States, the UK, and Canada. Yet, despite research on the domestic impacts of college expansion, little is known about its international spillovers.

We fill this gap by linking China's college expansion to downstream changes in the US higher education landscape, and the economies surrounding college towns. We explore the interaction between two of the world's most influential higher education systems: China and the US. While China has the largest university student population globally, American universities are renowned for their high quality of education, research production, and international influence. In this paper, we document how students from China played a significant role in driving major trends in US higher education, particularly in the boom of US STEM master's programs at research universities, and had broader regional impacts in stimulating the economy around college towns.

The raw trends are already striking: between 2005 and 2019, the number of Chinese students enrolled in US universities grew nearly sixfold, from around 62,000 to over 317,000, in parallel with the college expansion in China (Figure 1). By 2020, China had become the top country of origin for international students in the US, with its number of graduate students alone surpassing that of the second-ranked country, India (Figure A1). This rapid growth reshaped the US university sector and local economies surrounding college towns. In our analyses, we first examine how a domestic expansion in Chinese higher education affected Chinese student flows to the US, and then the subsequent impacts on the US higher education sector for American and other international students. But establishing causality is far from straightforward. Other concurrent forces, such as China's economic boom, evolving student aspirations, or shifts in US immigration policy, could also explain this surge.

To address the core identification challenge—isolating the causal impact of China's college expansion on US graduate education—we merge two granular administrative datasets. The first is a record of college admissions in China, capturing individual-level data and each student's home city, major, and admission year between 1999 and 2011. The second is the US Student and Exchange Visitor Information System (SEVIS), which tracks all foreign students enrolled in US institutions. We link these datasets across key dimensions: the student's city of origin in China, field of study, year of admission, and US destination institution. We assume a four-year lag between undergraduate admission in China and potential graduate enrollment in the US to align educational trajectories. Additionally, we construct a university-level panel using the Integrated Postsecondary Education Data System (IPEDS), focusing on the number and origin of graduate degrees awarded by US institutions.

Our identification strategy exploits the structure of China's centralized, quota-based college admissions system, which allocates enrollment slots by province, major, and year. We implement two complementary empirical approaches. First, we use a fixed effects framework to control for time-varying confounders. Specifically, we include city-by-year and major-by-year fixed effects, which absorb local economic trends that can increase demand for education abroad and field-specific shocks—such as changing demand for US graduate education, or evolving immigration policy—that might confound our estimates. Second, we employ a shift-share design to isolate plausibly exogenous variation in college expansion intensity at the city-major-year level. We construct predicted enrollment using the official province-major-year quotas, interacted with the pre-expansion distribution of students across cities within each province. Since the expansion is orthogonal to city-specific characteristics, this approach captures differential exposure to the expansion across cities and fields. We conduct several falsification tests and pre-trends analysis to help validate our research design.

Both strategies yield similar results. We estimate that a 10% increase in Chinese college admissions leads to a 4% rise in the number of Chinese graduate students enrolling in US institutions. In terms of levels, every additional 100 Chinese college graduates is associated with approximately 3.6 Chinese graduate students in the US. A back-of-envelope analysis suggests that China's college expansion can account for approximately 27% of the overall growth in Chinese graduate enrollment in the US between 2003 and 2015. The effect is notably stronger for students in STEM fields, and for those attending top-tier public research universities. The increase is also disproportionately concentrated at the master's level, consistent with observed trends in international enrollment.

Building on these findings, we then investigate the implications of rising Chinese master's student enrollment for other student populations in US universities. Specifically, we are interested in whether Chinese master's students crowd in or crowd out other students studying in the US, including both domestic and international students. The implications differ for these two groups. Prior research has documented that international students often contribute to the cross-subsidization of American domestic students (Shih, 2017). For other international students, however, the effect is ambiguous. On one hand, Chinese students may compete with them for limited seats, as all international students typically pay higher tuition. On the other hand, the growing number of Chinese students could incentivize universities to expand international services and launch new programs, which may ultimately benefit the broader international student population.

To investigate the impacts on US universities, we develop a second shift-share strategy at the university-year level. Here, we leverage variation in the baseline alumni networks between Chinese cities and US universities, and the change in Chinese enrollment quotas over time. The shifter is defined as the province-major-year college admission quota in China, while the share captures the baseline proportion of students attending a given US university relative to the total number of students from a specific province-major group admitted to Chinese colleges. The underlying assumption is that students from the same province and major tend to exhibit correlated preferences for particular American universities across years.

Our identification strategy follows the conditional exogenous shifter design proposed by Borusyak et al. (2022): we transform our university-year level analysis into province-major-year level, where we can further control for province-year and major-year fixed effects. This framework offers two key advantages over the traditional shift-share design. First, it helps control for potential demand-side confounding factors—for instance, US universities may prefer recruiting students from specific provinces or majors. Second, including these fixed effects enables us to isolate the effect of Chinese college expansion on international university outcomes by controlling for economic and educational changes within China. Specifically, province-year fixed effects absorb regional economic fluctuations, while major-year fixed effects account for shifts in major-specific preferences, both from the US side and from China. Together, these controls mitigate typical exclusion restriction concerns.

Our results reveal a notable pattern of crowd-in effects. Each additional Chinese master's student is associated with an increase of approximately 0.26 American master's students. We also find positive effects on other international students: one additional Chinese master's student is associated with an increase of 0.27 international undergraduates and 0.50 international master's students. While there is a minor crowding-out effect on other international Ph.D. students, the magnitude is small: each additional Chinese master's student displaces only about 0.09 international Ph.D. students. These findings suggest that the influx of Chinese master's students helps support the broader academic ecosystem—potentially by generating additional tuition revenue and prompting universities to expand program offerings. The effects are especially pronounced in STEM fields and at large public research universities, where such expansions are more likely to occur.

This heterogeneity has meaningful consequences. Public universities heavily rely on revenue from full-fee paying international students, which may be used to cross-subsidize local students paying in-state tuition (Bound et al., 2021). Further, the concentration on STEM majors in research universities may allow such colleges to expand science and engineering training and research output, with possible meaningful consequences to the US's capacity to innovate in the long run (Beine et al., 2024; Chen et al., 2023).

Our results suggest that students from China helped drive the US boom in STEM master's programs. The master's degree has emerged as a pivotal growth engine in US higher education, and STEM disciplines, especially computer and information sciences, drove much of this expansion. Master's awards in computer and information sciences surged by 145%, and those in health professions by 75% between 2011 and 2021 (National Center for Education Statistics, 2024). Financially, these programs play a crucial role in revenue generation, and are heavily dependent on international enrollment: between 2011 and 2017, doctoral degrees saw a more modest rise of 22% for international graduates, compared to a 68% increase at the master's level. Within STEM master's programs, the reliance on foreign students is even more pronounced: about 62% of master's degrees in computer science and 55% in engineering were awarded to international students (Bound et al., 2021). These trends reveal the critical importance of STEM-focused master's programs, not only as an academic vehicle but also as a financial cornerstone, driven in large part by international, especially Chinese, demand. Our findings show that college expansion in China has fueled this demand.

Furthermore, international students are not only consumers of higher education but also of the local goods and services that surround universities. We document suggestive spillover effects of Chinese master's students on local economies in college towns. An influx of Chinese students potentially stimulates economic activity by raising demand for housing, retail, and personal services. Using a similar empirical framework, we find that growth in Chinese enrollment increases job creation and reduces job destruction, leading to higher net employment growth. These results suggest that the influence of Chinese students extends beyond university campuses: while they strengthen the high-skilled education sector, they also generate demand that supports employment in lower-skilled, service-oriented parts of the local economy.

In sum, our goal is to link China's centralized effort to expand higher education with student flows to the US. While the reasons for the influx of international students are often attributed to US policies (Shih, 2017; Bound et al., 2020), we are among the first to connect this trend with an origin country's domestic college expansion program. Previous work examines the increasing trend of international students studying in the US from the perspective of both supply and demand for students. The demand for international students from US universities stems from much-needed tuition revenue (Shih, 2017; Bound et al., 2020; Chen, 2021) and foreign students' scientific output (Gaulé and Piacentini, 2013; Chen et al., 2023). Alternatively, some work sheds light on the supply of international students, focusing on US immigration policies (Bound et al., 2015; Shih, 2016; Amuedo-Dorantes et al., 2019, 2023), and increased foreign flows due to export-driven growth in China (Khanna et al., 2023). Our findings add a novel perspective that one country's educational policy can have ripple effects on the other side of the world.

We contribute to a growing literature on the impacts of international students, which has primarily focused on their interactions with domestic peers (e.g., Shih, 2017; Anelli et al., 2023; Costas-Fernández et al., 2023; Zhu, 2024). Our analysis centers on international master's students–

an increasingly important source of revenue for US universities–and provides causal evidence that Chinese master's students crowd in other international master's students.

Importantly, we also document the broader economic consequences of international student migration for local economies surrounding universities, which is less studied in the literature. International students contribute over $50 billion annually to US higher education exports (Bureau of Economic Analysis, 2025) and generate substantial demand for housing, retail, transportation, and personal services. We show that this inflow of students stimulates job creation in college towns, highlighting the wider economic significance of global higher education flows.

Our study enriches a growing literature that has evaluated the domestic impacts of China's college expansion program, primarily on human capital accumulation (Rong and Wu, 2020; Huang et al., 2021; Qin and Kong, 2021; Huang et al., 2022; Wang et al., 2022; Fu et al., 2022) and firm behavior (Che and Zhang, 2018; Chen et al., 2021; Feng and Xia, 2022; Kong et al., 2022; Feng et al., 2023; Ma, 2024), few have explored the impacts beyond China. While we focus on the US as the destination country, our findings can also be relevant for other major destination countries for Chinese students, such as the UK, Canada, and Australia.

Finally, our findings have implications for current policy debates about immigration and the role of universities in American progress. Geopolitical tensions, particularly between China and the US, which already reshaping the landscape of higher education. Recent studies document how these tensions affect US-based scientists and the flow of Chinese PhD students to the US in STEM fields (Jia et al., 2024; Flynn et al., 2024). Our results suggest that international master's students are also likely to be on the front line, facing new challenges and pressures of adaptation in the years ahead.

The remainder of the paper is structured as follows. Section 2 describes China's college admission system and its expansion since 1999. Section 3 outlines our data sources and the procedures used to merge the databases. Section 4 addresses our first research question: to what extent did China's college expansion program contribute to the rise in Chinese graduate students studying in the US? Section 5 answers our second question: how has the influx of Chinese graduate students affected American universities? Section 6 extends the analysis to college town economies to examine broader regional impacts. Section 7 concludes.

2 Chinese Higher Education: Admissions, Expansion, and International Migration

2.1 The Centralized Quota System in College Admission

The college admission system in China is highly centralized, with the national college entrance exam scores, commonly known as the "gaokao", serving as the primary criteria for university admission. Universities and colleges use the gaokao scores to rank applicants and make admission decisions. The most prestigious universities in China typically have the highest gaokao score requirements, making admission to these institutions extremely competitive. The gaokao exams are different across provinces, and students need to be in their Hukou province to take the exam.[1]

College enrollment in China is regulated through a quota system, with quotas set by the Ministry of Education at the province–major–year level. The allocation follows political economy: major metropolitan areas such as Beijing and Shanghai are granted higher quotas per capita, while provinces with large ethnic minority populations, such as Xinjiang and Tibet, also receive preferential treatment. In contrast, populous provinces in the central regions, such as Shandong, Jiangsu, Henan, and Anhui, tend to receive among the lowest quotas relative to their population size. The criteria for assigning quotas across majors are less transparent, but likely reflect provincial development priorities and the geographic distribution of universities with different areas of strength.

Since far more students sat for the college entrance exam than the available quota, quotas were always binding and thus governed variation in admissions at the province-major-level (Figure A2). For our analysis, the assumption is that province-major-year quotas are orthogonal to specific city-level characteristics in China and to specific university characteristics in the US, an assumption that is not overly restrictive in this context.

2.2 Chinese College Expansion from 1999

China's large-scale expansion of higher education began in 1999. Before then, enrollment growth had been gradual, guided by the principle of "steady development." The late 1990s, however, brought new pressures: the Asian financial crisis, widespread layoffs from state-owned enterprises, and growing numbers of urban youth entering the labor market. In this context, expanding higher education was seen as a way to absorb rising numbers of urban youth, stimulate domestic demand, and accelerate the country's transition toward a more knowledge-intensive economy (Wang, 2014).

The expansion was carried out through substantial increases in admission quotas, which are centrally determined by the Ministry of Education. In this process, the number of higher educa-

[1] Fewer than 3% of students are admitted before the college entrance exam, either as excellent athletes or winners of national competitions in several STEM majors.

tion institutions rose from about 1,000 in 1999 to more than 2,000 by the 2010s, while annual new enrollments grew from just over 1.1 million in 1998 to nearly 8 million by 2018. For four-year universities specifically, admissions increased from around 0.9 million in 1998 to nearly 4 million by 2015.[2] College graduates from these four-year universities are the focus of our study, as relatively few graduates of two- or three-year colleges pursue graduate studies abroad.

Two notable features of Chinese higher education are worth highlighting. First, the system follows the principle of being "strict in entry and relaxed in exit," meaning that once admitted, very few students drop out or fail to graduate (Jia and Li, 2021). As a result, college enrollment is a close proxy for the number of college graduates.

Second, both the broader education system and the college expansion policies place strong emphasis on STEM fields. Panel A of Figure A3 shows that while enrollments increased across all majors, STEM fields grew most rapidly, reflecting the government's prioritization of science and technology as drivers of economic modernization. Our analysis exploits this variation across majors as a key source of identification.

2.3 Chinese Students Studying Abroad

China's wave of overseas study began in the late 1970s, when the government first permitted a small number of students to study abroad as part of the reform and opening-up period. These early cohorts were almost entirely state-sponsored graduate students in science and engineering fields, often sent to the US, Japan, and Europe for advanced training. Beginning in the 1990s, however, a profound shift occurred: the rapid rise of self-financed students. As household incomes grew and restrictions on overseas study were relaxed, large numbers of Chinese students began to pursue education abroad at all levels, from undergraduate to doctoral study.

By the 2000s and 2010s, China had become the world's largest source of international students. According to Ministry of Education statistics, more than 660,000 Chinese students went abroad in 2018 alone, and cumulative totals exceeded five million. Roughly 80% of these students financed their own studies, in contrast to the early reliance on state sponsorship. The US has consistently been the top destination, especially for graduate education, followed by the United Kingdom, Australia, Canada, and Japan.

Eligibility for graduate study in the US requires a four-year accredited undergraduate degree, strong academic performance, and standardized test results. Doctoral students are frequently supported through fellowships, research assistantships, or teaching assistantships, while master's programs are more often self-funded. In addition, successful applicants must secure an F-1 student visa, which provides the information we use to measure study in the US.

[2] Among four-year universities, the most prestigious institutions expanded modestly, whereas mid- and lower-tier universities accounted for the bulk of the growth.

3 Data

The two primary datasets used in our analysis are China's College Admission Records, and the Student Exchange and Visitor Information System (SEVIS) dataset. The key variation we exploit throughout the paper is China's college admission quota. The SEVIS dataset provides visa records for all international students studying in the US, allowing us to distinguish foreign student enrollment by home country, university destination, level of study, and field of study.

Additionally, to examine the impacts at the university level, we incorporate university-year panel data from the Integrated Postsecondary Education Data System (IPEDS) and data from the National Center for Science and Engineering Statistics (NCSES) provided via the National Science Foundation (NSF). We also draw on data from the Business Dynamics Statistics (BDS) to analyze the effects on local economic activity.

3.1 Chinese and International Student Data

China's College Admission Records. We draw on the near-universe of Chinese college admission records from 1999 to 2011, compiled from multiple sources.[3] To link with data on US universities, we aggregate individual-level admission records by Hukou city, college major, and admission year, yielding a panel that covers 31 provinces (334 cities), 15 majors, and 13 years. Since admission quotas are set at the province-major-year level, we further aggregate the data accordingly to recover quota information.

SEVIS Database. International students studying in the US must obtain an F or M visa. The M visa is limited to vocational and nonacademic institutions, while the F visa covers a broader range—from primary and secondary schools to higher education, seminaries, conservatories, and language training programs. Our study focuses exclusively on graduate students holding F visas.

We obtain individual-level data from the Student Exchange and Visitors Information System (SEVIS), a web-based platform used by the Department of Homeland Security (DHS) to track nonimmigrant students and exchange visitors. The data were accessed through a Freedom of Information Act (FOIA) request.

The dataset includes visa records for all foreign students by year of matriculation from 2000 to 2015.[4] It contains information on each student's permanent address, gender, university, level, field

[3] We combine several data sources to construct admission records over this period. A couple of gaps remain: there is no information for 2004, and records are missing for Heilongjiang in 2001, Jiangsu from 2009 to 2011, Zhejiang in 2011, Hainan in 2002, and Tibet from 1999 to 2003. Because our design relies on initial shares from 1999, we exclude Tibet from our analysis. For the remaining gaps, we impute province-major-year quotas using linear interpolation. As we will show, our findings are unlikely to be influenced by these gaps.

[4] We access data on Chinese students from 2000 to 2015, and on all international students from 2004 to 2015.

of study, program start and end dates, and sources of financial support. We classify students' majors based on their program descriptions and use the matriculation year and major as key variables. For Chinese students, we treat the permanent address listed on the Form I-20 as a proxy for their Hukou city, enabling us to match city names with standardized city codes.[5]

3.2 US University-level Outcomes

Integrated Postsecondary Education Data System (IPEDS). The Integrated Postsecondary Education Data System (IPEDS), maintained by the National Center for Education Statistics (NCES), collects comprehensive data on US colleges, universities, and technical institutions, including enrollment, graduation rates, finances, and faculty characteristics. For our analysis, we primarily use the financial data on universities.

The National Center for Science and Engineering Statistics. The National Center for Science and Engineering Statistics (NCSES), a principal federal statistical agency within the National Science Foundation (NSF), provides comprehensive data on US higher education institutions.[6] This dataset includes information on degree completions by level and field of study, as well as by students' citizenship and race. It also enables us to track the expansion of the number of programs offered by each institution by degree level.

In Figure A4, we present trends in degree completions by American and international students across three levels: bachelor's, master's, and doctoral degrees. For both bachelor's and master's degrees, the number of degrees awarded to international students increased more sharply than for American students. In contrast, at the doctoral level, we see a sharper increase in Americans, particularly between 2008 and 2010.

Following Kelchen and Barrett (2024), we use the 4-digit Classification of Instructional Programs (CIP) codes to track changes in program offerings. Although some institutions may offer multiple distinct programs under the same 4-digit CIP code, this approach is the best source for tracking program-level changes over time.

3.3 County-level Outcomes

The Business Dynamics Statistics (BDS) is a dataset compiled by the US Census Bureau that tracks the dynamics of US businesses over time. It provides detailed annual data on firm age, firm size,

[5]The Form I-20 is issued by SEVP-certified schools and documents a student's F or M visa status. It includes the student's personal and academic details as required by the US Department of Homeland Security.

[6]For more information, see https://ncsesdata.nsf.gov/home. We use the dataset sourced from the IPEDS Completions Survey from the Department of Education.

job creation, job destruction, and business survival at various geographic and industry levels. We use the data at the county-year level to track the evolution of the economy.

We focus our county-level analysis on college-town counties, where the influence of Chinese students is likely to be more significant and dominant. A college town is a city or town where a university significantly influences the local economy and culture, often with students making up at least 20% of the population. The university may be the largest employer, and many businesses cater primarily to students. These towns are distinct from student quarters in larger urban areas, as the university's presence shapes the entire community. We select American college towns following the definition on Wikipedia.[7]

3.4 Linking the Databases

China's College Admission Records and the SEVIS Database. We merge the college admission dataset with the SEVIS dataset based on students' city of origin, major, and year. To link the two datasets, we use the city listed in the SEVIS database as the student's Hukou city, following the assumption that the permanent address reflects their place of origin.[8]

Major is a key dimension in our study, but the college admission and SEVIS databases' descriptions do not align perfectly. We classify majors based on available descriptions in both datasets. Yet, students may switch fields between undergraduate and graduate studies, which could introduce noise. To address this, we use two levels of classification: a detailed scheme for the primary analysis and a broader one for robustness checks. The broader classification includes four major groups-STEM, Economics and Business, Social Science, and Humanities—under which we further group 15 subfields.[9] We present trends by the four broader majors in Figure A3.

To align years, we assume students spend four years in undergraduate studies before entering graduate school in the US, implying a four-year lag between admission and US graduate enrollment. Our college admission data spans 1999–2011, corresponding to SEVIS graduate records from 2003–2014. In total, our matched dataset covers 333 Chinese cities, 15 majors, and 13 years.

The SEVIS Database and US University- and County-level Outcomes. To analyze American university outcomes, we link the SEVIS database with other university-level datasets. Since SEVIS uses a unique university code and others use "UnitID," we match them by university name,

[7] Details of college towns definition are on Wikipedia and the list of American college towns is on Wikipedia.

[8] While this assumption holds for most students, some may report their college address, particularly those studying in Beijing or Shanghai, which host a large share of college students. To address this potential bias, we conduct additional analyses excluding these two cities.

[9] It includes including Math and Statistics, Science (including physics, biology, and chemistry), Electronic Engineering and Computer Science (EECS), Agriculture and Environmental Science, Psychology, General Engineering, Civil Engineering and Architecture, Economics, Business, Law, Education, Other social science, Literature, History, and Other Humanity.

using dataset-provided similarities and manual cross-checking for validation. Of all universities in the SEVIS data, only 2.5% (28) of universities could not be linked, yielding a sample of 1,104 universities. For some analyses, we aggregate the university-level enrollment data to the county level based on their locations, and link it with the BDS using county-year identifiers to study broader economic effects.

3.5 Summary Statistics

Chinese City-major-year-level Analysis. In the first part of the analysis, the unit of observation is Chinese city-major-year combinations, covering 333 Chinese cities, 15 majors, and 13 years. Panel A of Table A1 presents summary statistics for the main variables used in our analysis.

College Admission denotes the number of undergraduate admissions at the city-major-year level, based on Chinese college admission data. We observe 56,820 unique combinations, and the average number of admissions per city-major-year is 426, with 2% of observations equal to zero, indicating no admissions in those cases.

Chinese Grad measures the number of students from a given Chinese city admitted to US graduate programs in a specific major and year. Its mean is 4.87—much lower than College Admission—with 60% of observations equal to zero, reflecting the scarcity of students in many city–major–year cells. By degree level, Master's students outnumber Doctoral students, with means of 3.53 and 1.34, respectively.

We also examine the distribution of students across US university types. While Chinese students are evenly split between public and private institutions, a disproportionate number attend R1 universities, relative to R2, Doctoral/Professional, and Master's-level universities.[10]

US University-level Analysis. To understand the spillover effects of Chinese students on non-Chinese student enrollment in US universities, our second analysis focuses on universities with at least one Chinese graduate student during our study period, 2000-2015. Constructing the main sample for analysis requires identifying research universities consistently available in the IPEDS 2003-2015 surveys, and in the SEVIS database from 2000-2015. As mentioned above, this yields a panel of 1,104 universities.[11]

Panel B of Table A1 presents statistics for Chinese students at the university-year level, based on the sample constructed above for 2003–15. The baseline sample includes 14,358 observa-

[10] US universities are classified using the Carnegie Classification system. R1 and R2 institutions are doctoral universities with very high and high research activity, respectively, while Doctoral/Professional universities focus on awarding professional doctorates, and Master's-level universities primarily offer master's degrees with limited or no doctoral programs.

[11] Among these universities, 531 universities had at least one Chinese graduate student before 2003 (i.e., prior to China's college expansion in 1999, corresponding to graduate students coming to the US in 2003.)

tions, corresponding to unique university-year combinations. On average, each university admits approximately 20 Chinese graduate students annually, with master's students (14.5) far outnumbering doctoral students (5.5). Additionally, universities admit around 4.3 Chinese undergraduates per year. Decomposing graduate enrollment by field, we find that Chinese STEM students exhibit a higher mean (10.7) and variance (43.5) than those in other fields (9.3 and 34.6).

College-town County-level Analysis. We focus on college-town counties to study the broader economic impacts of Chinese students. This yields 425 unique counties in the US. Panel C of Table A1 presents summary statistics for Chinese graduate students at the county-year level. The mean number of total graduate students is 37, with 26 students at the master's level and 11 at the doctoral level.

4 College Expansion and Chinese Graduate Student Flow

Our first objective is to understand the relationship between the expansion of Chinese colleges and the flow of Chinese students to American graduate schools. To do so, we exploit variation in admission quotas to predict changes in undergraduate enrollment at the city-major-year level and link these to Chinese graduate student flows to the US four years later.

4.1 Empirical Strategy

The Baseline Poisson Model. Leveraging granular-level data, we start with a simple fixed effects model that considers trends such as city economic development as a baseline of our analysis (Hausman et al., 1984). The Poisson specification is as follows:

$$\mathbb{E}(ChineseGrad_{cmy}) = exp(\gamma_{cy} + \phi_{my} + \beta_1 ln(CollegeAdmit_{cmy-4})), \tag{1}$$

where c denotes the Chinese city, m the major, and y the year. $ChineseGrad_{cmy}$ is the number of Chinese graduate students in the US, and $CollegeAdmit_{cm,y-4}$ is the number of Chinese college students admitted four years earlier (which closely approximates the number of graduates). γ_{cy} and ϕ_{my} represent city-year and major-year fixed effects, respectively.

The primary coefficient of interest in our study is β_1, which represents the elasticity between the flow of students admitted by Chinese colleges and the flow to US graduate programs. We reported clustered standard error at the city level to allow for arbitrary correlations within a city.

To accommodate zeros in the dependent variable without transforming its scale (Wooldridge, 2010; Cohn et al., 2022; Chen and Roth, 2024), we employ a Poisson model.[12] As shown in Table A1, while only 2% of the independent variable values are zero, the dependent variable contains 60% zeros given the distribution of students studying in the US across cities, years, and majors.

We include both city-year and major-year fixed effects in our baseline specification. City-year fixed effects account for confounders stemming from local demographic and economic dynamics. For example, rising incomes increase demand for US education, and wealthier cities that developed earlier are disproportionately likely to send students abroad (Khanna et al., 2023). At the same time, such cities often possess stronger educational resources, which improve student performance on the college entrance exam. By absorbing time-varying city-level characteristics, city-year fixed effects help address these potential confounds.

Major-year fixed effects control for systematic differences across fields of study. US demand for certain majors and China's supply of students by field may evolve simultaneously. STEM fields, in particular, have more globally standardized curricula, while social sciences and humanities are shaped by local ideological and cultural contexts. Moreover, the Chinese government has consistently prioritized STEM in its quota allocations, viewing it as central to economic development. US visa policy reinforces this emphasis: the Optional Practical Training (OPT) period has been extended twice in recent years, disproportionately benefiting STEM graduates. Since job prospects strongly influence international study decisions (Bound et al., 2015; Shih, 2016; Amuedo-Dorantes et al., 2019, 2023), STEM students are especially responsive to such policy shifts. Major-year fixed effects, therefore, absorb these systematic and policy-driven trends.

As suggestive evidence, Figure A5 illustrates the relationship between $log(ChineseGrad_{cmy})$ and $log(CollegeAdmit_{cm,y-4})$ after partialling out these fixed effects. The relationship is positive and approximately linear, supporting the Poisson specification.[13]

An Instrumental Variable Approach. Our baseline model controls for city-year and major-year fixed effects. While these fixed effects likely absorb a significant portion of confounding factors, concerns may remain regarding the baseline identification strategy. For instance, if certain cities consistently produce well-educated students in specific majors, these cities may send more students to both Chinese domestic colleges and US graduate schools, potentially biasing our results. To further address any remaining concerns, we leverage the admission process at the province-major-year level to construct an instrumental variable and account for potential omitted variables.

To construct the instrument, we begin by defining two variables: $Quota_{pmy}$ and $Share_{cm}$. The variable $Quota_{pmy}$ represents the province-major-year level quota assigned by the Ministry of Edu-

[12] We apply the Pseudo-Poisson Maximum Likelihood with High-Dimensional Fixed Effects (PPMLHDFE) (Correia et al., 2020). The consistency of the Poisson estimator only requires the correct specification of the conditional mean of the dependent variable (Gourieroux et al., 1984; Wooldridge, 1999).

[13] Since all the variables contain zeros, we use the inverse hyperbolic sine formulation to ease visualization.

cation, which is equal to the sum of $CollegeAdmit_{cmy}$ across all cities within province p. The variable $Share_{cm}$ captures the exposure of each city-major pair to the policy at the onset of the reform in 1999, as defined in Equation (2). Under our design, a higher value of $Share_{cm}$ indicates that a given city-major pair was more exposed to the policy and, consequently, more affected by the province-level quotas during the reform period. Finally, we construct our instrument $\widehat{ChineseAdmit}_{cmy}$ by interacting $Quota_{pmy}$ and $Share_{cm}$.

$$Share_{cm,1999} = \frac{CollegeAdmit_{cm,1999}}{Quota_{pm,1999}} \tag{2}$$

$$\widehat{ChineseAdmit}_{cmy} = Quota_{pmy} \times Share_{cm,1999} \tag{3}$$

To test the relevance assumption of our IV approach, we examine whether the interaction of provincial level quota and the city-major share in 1999 drives meaningful variation in $CollegeAdmit_{cmy}$. The exclusion restriction requires that the quota and share interaction affect Chinese cross-border flows only via local Chinese undergraduate enrollment, after conditioning on city-year and major-year fixed effects. Although the exclusion restriction cannot be directly verified, we conduct falsification tests to show that potential violations are unlikely to pose a serious concern.

To estimate the IV Poisson Model, we employ a two-step approach. First, we regress the endogenous independent variable $log(CollegeAdmit_{cmy})$ on the instrument $\widehat{ChineseAdmit}_{cmy}$ using a linear model. To obtain a consistent estimate for β_1 in Equation (1), we apply a control function approach (Wooldridge, 2015). Specifically, we include the residuals from the first-stage regression into the second stage, which generates the results of the IV approach. We employ the Poisson model for our second stage. We control for the city-year and major-year fixed effects as in the baseline throughout the estimation.

Figure A6 plots the residualized first-stage and reduced-form relationships after partialing out the two fixed effects and applying a log transformation. Both show a positive association between the instrument and Chinese admissions, and between the instrument and Chinese graduate student enrollment in the US.

4.2 Results

Main Results. Column (1) of Table 1 shows the results from the baseline Poisson model. The elasticity coefficient, 0.405, implies that a 10 percent increase in Chinese college admissions is associated with a 4.05 percent increase in Chinese students pursuing graduate studies in the US. We report results from additional IV specifications in Table A2 and from a level–level specification in Table A3. The same specification in the level-level specification yields a coefficient of 0.0361, indicating that an increase of 100 Chinese college admissions is associated with 3.6 additional Chinese graduates in the US.

Columns (2) and (3) report estimates from the first-stage regression with our IV approach. While column (2) includes only the instrument, column (3) additionally controls for $Quota_{pmy}$ and $Share_{cm,1999}$. Both specifications show a strong first-stage relationship, with F-statistics of 64.87 and 77.26, respectively. Reduced-form results are reported in columns (4) and (5), with estimated coefficients of 0.256 and 0.329. Finally, columns (6) and (7) present the IV estimates with and without controls, yielding effect sizes of 0.395 and 0.408, both of which are closely aligned with the Poisson baseline result reported in column (1).

In Table 2, we report estimates across different subsamples: (1) excluding Beijing and Shanghai, (2) restricting to large cities with populations above 5 million (80 cities), and (3) restricting to smaller cities with populations below 5 million. The corresponding coefficients are 0.440, 0.457, and 0.335, respectively. These results suggest that the elasticity is stronger in larger cities than in smaller ones. Since a large city also produces more college students than a small city, this heterogeneity highlights the relatively greater role of more developed urban areas in supplying Chinese students to US universities.

We also provide a robustness check by aggregating the data at the provincial level, as the policy is targeted at the province level rather than the city level. The dataset includes 31 provincial administrative units, including the four municipalities of Beijing, Tianjin, Shanghai, and Chongqing. We present the results in Table A4, and like the baseline analysis, we report the results using the whole sample, sample without Beijing and Shanghai, and samples of large provinces. The findings are consistent across the three samples. Our preferred specification is province-year and major-year fixed effects. At this more aggregate level, the estimated elasticity is 0.343.

We also examine how the effect changes over time by splitting the sample into four periods (2003-05, 2006-08, 2009-11, and 2012-15) and present the coefficients for each period, in Panel A of Figure A7. The coefficients are sizable across periods, but larger during 2006-2011.

Patterns by Degrees, Fields, and Institutions in the US. To assess the differential impact of the Chinese college expansion program, we examine heterogeneity along several dimensions using the IV specification (column (7) of Table 1), as shown in Figure 2. First, we disaggregate the Chinese graduates' outcome into Chinese Master's and Doctoral students, finding that the elasticity is higher for doctoral students than master's students. However, because the mean level of master's students (14.5) is much higher than that of doctoral students (5.4), master's students account for over 85% of the induced increase in Chinese graduate student enrollment.

We also split the sample by field of study and find that STEM students exhibit significantly greater elasticity than non-STEM students. This difference may arise from the greater consistency in STEM curricula between China and the US. In contrast, non-STEM fields such as political science and law are more region-specific, creating barriers for Chinese students pursuing graduate studies in those areas.

Next, we explore heterogeneity by university characteristics by refining the outcome variable to reflect flows into specific types of US institutions. We find only slightly larger effects for public universities. When stratifying by university quality using the Carnegie classification (R1, R2, Doctoral/Professional, and Master's only), the effect is most pronounced for R1 institutions, indicating that Chinese graduate students are disproportionately concentrated in top-tier universities and suggesting strong student quality.

Falsification Tests and Pre-trends Analysis. We conduct three sets of analyses to further validate our research design. First, as suggestive evidence, we present a residualized scatterplot in Panel A of Figure 3, constructed from both the pre-reform (graduate school admission years 2000–2003) and post-reform (2003–2015) periods, using a log-log specification.[14] Specifically, we partial out the fixed effects described above and plot the residualized variables on the x- and y-axes. A clear positive relationship emerges in the post-reform period. By contrast, because college admission data are unavailable for the pre-reform period, we assign the variable from 2000–2003 to a random year between 2012 and 2015 (while keeping the city and major fixed) and retain the original variable for graduate school admission. This placebo exercise yields no meaningful correlation, suggesting that our main findings are unlikely to be driven by pre-existing relationships.

Second, we generate a placebo variable at the city level by randomly reassigning the city associated with college admissions. We include both the actual and placebo variables and repeat this procedure 100 times, each time drawing a random placebo city from the sample. We plot the resulting distribution of the coefficients in Figure 3. The distribution is centered around zero, confirming that the placebo variable does not confound our results. This evidence supports our interpretation that the findings are driven by city-level increases in college admissions induced by the quota system.

Third, we conduct a test analogous to an event-study design to examine pre-trends. Since our treatment is not a one-time event, a standard event-study approach is not feasible. To approximate it, we define treatment at the city-major level as the percent change in Chinese undergraduate admissions from 1999 to 2003 (i.e., the four years immediately following the policy). The outcome is the number of Chinese graduate students in the US four years after undergraduate enrollment. Using data beginning in 2000, which corresponds to undergraduate admissions in 1996, we can assess pre-trends prior to the reform.

Panel B of Figure A7 shows no significant effects in 2000–2002, suggesting that our main

[14] We use the inverse hyperbolic sine to replace the log to accommodate zeros.

results are unlikely to be driven by pre-existing differential trends. From 2003 onward, however, we observe consistent positive effects.

Back-of-envelope Analysis. We conduct a back-of-the-envelope calculation to interpret the magnitude of our estimated effect, using the elasticity of 0.408 from our preferred specification. In 1999, the number of college admissions in China was 0.9 million, and the total number of admissions in 2011 reached 3 million, a 2.4-fold increase. Applying this growth to our estimated elasticity implies that the Chinese college expansion accounts for about 27% of the rise in Chinese graduate student inflow to the US.

This calculation, however, requires caveats, as it is based on our identification strategy where we leverage *relative* differences across city-major-year observations, with common increases in the quota absorbed by the fixed effects. Our calculation can be under-estimated, if part of the common increases can be attributed to college expansion.

5 Impacts on non-Chinese Student Enrollment

We next examine how the influx of Chinese students influences the enrollment of non-Chinese students in US universities.[15] The effect is theoretically ambiguous. On the one hand, if university capacity has not grown, the increase in Chinese master's students could displace other applicants. On the other hand, the substantial tuition revenues from Chinese master's students may enable universities to cross-subsidize other programs, thereby expanding opportunities for non-Chinese students.

To study this question, we implement a shift-share design at the university level. Guided by our earlier results, we concentrate on master's students, who account for over 85% of the induced increase in Chinese graduate student enrollment.

5.1 Empirical Strategy

To explore the link between the increase in Chinese master's students and non-Chinese students in US universities, we start with the following OLS specification:

$$Y_{ut} = \beta_0 + \beta_1 \text{ Chinese Masters}_{ut} + \alpha_u + \delta_t + \varepsilon_{ut}, \tag{4}$$

where Y_{ut} denotes the outcome for university u in year t, α_u are university fixed effects, and δ_t are year fixed effects.

[15] We show the change in the raw data in Figure A8. Overall, the number of non-Chinese master's students increases alongside Chinese master's students, while the number of non-Chinese doctoral students remains relatively stable.

We use a level specification in this section to facilitate interpretation and comparison to the existing literature. To be cautious, we trim the outcome variable at the top and bottom 1%, thereby reducing the risk that extreme values drive our results.

To address the challenge that Chinese Masters$_{ut}$ is endogenous, we employ a shift-share design at the university level. Here, we leverage the fact that college admission quotas in China are assigned at the province-major-year level and are orthogonal to specific characteristics of US universities. Unlike in the first part of the analysis, the share here is based on the historical distribution of students from a province-major across universities. For example, suppose that before the expansion, a larger fraction of Economics students from Shandong attended UCLA rather than UCSD. When Shandong's Economics quota increases, we assume that a larger fraction of all Shandong Economics students going abroad will also attend UCLA rather than UCSD. We test this assumption empirically. To maintain a strong first stage, we group majors into four broad categories introduced earlier. The first-stage design is defined as:

$$\begin{aligned} \text{Chinese Masters}_{ut} &= \gamma_0 + \gamma_1 \, ShiftShare_{ut} + \alpha_u + \delta_t + \varepsilon_{ut}, \\ ShiftShare_{ut} &= \sum_{pm} Quota_{pmt} \times Share_{pmu,t-5}, \end{aligned} \tag{5}$$

where $Share_{pmu,t-5}$ is the share of master's students from province–major pm who attended university u five years earlier.[16]

We include university and year fixed effects to capture differences in university attractiveness and time trends. In addition, following recent work on the identification assumptions of Bartik instruments (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022, 2025), we also incorporate province–year and major–year fixed effects, ensuring that $Quota_{pmt}$ is as close to quasi-random as possible.

To implement these additional fixed effects at the university-year level, we adopt the method of Borusyak et al. (2022). Specifically, we create the corresponding indicators for province-year and major-year fixed effects, then reweight them using the same $Share_{pmu,t-5}$. Because the shares are incomplete by construction, we also include the sum of the shares in the regression to account for differences in overall exposure.

A final concern is that shift-share IV inference may suffer from correlation in residuals across observations with similar exposure shares. To address this, we follow Borusyak et al. (2022) and transform the dataset to the shifter level, estimating a shifter-level regression to obtain exposure-robust standard errors. This complements our main university-level analysis, where standard errors are clustered at the university level.

[16] Our results are robust to using longer lags, though the number of years available for estimation falls.

5.2 Results

First-Stage Estimates. We present the first-stage results in Table A5 to assess the relevance of our instrument. Columns (1) through (4) progressively add controls: Column (1) includes no controls; Column (2) adds the sum of shares; Column (3) includes province-year and major-year fixed effects. Our preferred specification, shown in Column (3), includes both province-year and major-year indicators, which mitigate potential influences of omitted variables. The F-statistics vary between 32.7 and 91.6, indicating strong instrument relevance and supporting the validity of our constructed shift-share instrument.

American Students. Panel A of Table 3 reports estimates of American student enrollment by degree level, using both the OLS and IV specifications introduced in Section 5.1. We adopt the more conservative university-level clustered standard errors as our baseline, while Table A6 reports results with shift-share standard errors. We also provide results from additional specifications for bachelor's, master's, and doctoral degrees in Table A7–A9.

Both the OLS and IV estimates indicate a positive association at all three degree levels, though the IV estimates are less precise. For master's students, the OLS estimate implies a coefficient of 0.441, while the IV estimate falls to 0.264. This suggests that each additional Chinese master's student is associated with an increase of roughly 0.26–0.44 American master's students. A back-of-the-envelope calculation indicates that Chinese master's students account for about 10% of the total increase in master's degrees awarded to American students.

International Students. Data on international students are obtained from the SEVIS database, using the year of status activation as a proxy for enrollment year. We separate other international students from Chinese international students.

In Panel B of Table 3, we report the effects on international student enrollment by level of study, using both OLS and the IV methods consistent with the specifications described in Section 5.1. Again, we provide the main results with standard errors clustered at the university level in Table 3, and results from the shifter-level regression in Table A10, following Borusyak et al. (2022). We also provide results from additional specifications for undergraduate, master's, and doctoral students in Tables A11–A13.

We find significant positive effects at the undergraduate and master's levels, and a slightly negative effect at the doctoral level. The OLS estimate for international undergraduates is 0.09, while the IV estimate is 0.27, indicating that the enrollment of one additional Chinese master's student is associated with an increase of 0.09 to 0.27 international undergraduate students.

The effect is larger at the master's level, where one Chinese master's student leads to an increase of 0.18 (the OLS estimate) to 0.50 (the IV estimate) international master's students. Overall, these results suggest that the influx of Chinese master's students may enable universities to expand master's programs. At the doctoral level, in contrast, we find small but negative coefficients, -0.02 (OLS) and -0.09 (IV), indicating that there can be a crowding-out effect on other international students, likely because enrollment capacity at the doctoral level is more limited.

Patterns by Fields and Institutions. We present a set of heterogeneity analyses using the IV specification, including province-year and major-year indicators in Figure 4. We provide results for both American (Panel A) and other international students (Panel B) by field and university type.

We begin by comparing STEM and non-STEM fields to examine how universities allocate program slots in response to an influx of Chinese master's students. As shown in Panel A, the positive effect on STEM master's programs is estimated more precisely than for non-STEM programs, although the effect sizes are similar. For other international students, we observe substantial heterogeneity at the master's level: the effect on STEM master's enrollment is significantly larger (approximately 0.5) compared to non-STEM (approximately 0.15). This finding implies that the crowding-in effect is stronger in STEM fields, which is consistent with the program expansion we will document later.

We further examine heterogeneity by university type, comparing public and private institutions given their distinct funding structures. We find a substantially larger positive effect on master's student enrollment in public institutions, both for American and other international students, compared to private institutions. This suggests that public universities are more likely to expand overall program capacity in response to increased demand. In contrast, private universities, which typically adhere to stricter student–faculty ratios, appear less inclined to expand enrollment. In addition, we find that R1 institutions exhibit significantly larger positive effects on master's students, both American and international, than non-R1 universities.

5.3 Falsification Tests and Pre-trends Analysis

We conduct three exercises of falsification tests and pre-trends analysis to validate our research design. First, following Borusyak et al. (2022), we examine pre-trends by testing whether changes in the outcome variable in the pre-shock period are correlated with the future value of the shift-share variable. This is analogous to tests of parallel trends in difference-in-difference research designs. To facilitate the analysis, we construct a treatment variable using the long-difference version of the shift-share instrument defined in Equation (5), measuring the change from 2003 to 2015.

$$\Delta Y_u = \beta \Delta ShiftShare_u + \eta ProvYear_u + \phi MajorYear_u + \gamma SumShares_u + \varepsilon_{ut} \tag{6}$$

We conduct long-differences analyses, as specified in Equation (6), at the university u level. The idea is to use $\Delta ShiftShare_u$ to predict changes in outcomes between the pre-reform (2000–2003) and post-reform period (2003–2015). We hypothesize that changes in the outcome variable in the pre-shock period are not correlated with the future value of the shift-share variable.

In addition to the primary treatment variable, we control for $ProvYear_u$ and $MajorYear_u$, consistent with the panel data specifications in Section 5.1. Since the analysis is at the university level, we reweight the indicators using shares from the 2000–2003 period to vary by university u, following (Borusyak et al., 2022). We also control for the sum of shares and cluster standard errors at the university level.

We present the results in Panels A and B of Figure 5, showing residualized changes after controlling for province and major indicators, as well as the sum of shares. We present the results for non-Chinese students, disaggregated by level of study.[17] For all master's outcomes, we observe no effect in the pre-reform period, but a positive effect in the post-reform period. In contrast, doctorate outcomes show no significant impact in either period.[18]

Following the same logic, we test for pre-trends using other university-level indicators. The results are presented in Table A14. We find that $\Delta ShiftShare_u$ has no effect on changes in various pre-reform characteristics, including the percentage of freshmen from out-of-state, the number of non-resident alien undergraduates, availability of non-need-based aid, and the provision of master's and doctorate degrees. These results further validate our research design.

Second, we construct a placebo outcome by randomly reassigning the outcome using another university's data in the same year. We perform this test 100 times for both American and other international master's students. As shown in Figure 6, the distribution of placebo coefficients is centered around zero. It is much smaller than our estimated effect, confirming that the placebo does not drive our results.

Event Study. Additionally, we conduct a pre-trends test analogous to an event study. Again, to approximate the one-time shock, we define the university-level treatment as the growth in the first five years of $\Delta ShiftShare_u$ (2003–2008). To maintain consistency with the previous analysis, we include interactions between the year indicators and the reweighted university-level province-year and major-year indicators to account for the corresponding fixed effects. We also control for the sum of shares and cluster the standard errors at the university level.

This approach estimates effects at each event time and serves two purposes: first, to test for parallel trends by examining whether other factors drive differential trends between universities with varying treatment; and second, to trace the dynamic effects of the reform over time.

[17] SEVIS data on other international students spans 2004–2015. To examine pre-trends, we calculate their numbers by subtracting Chinese students (from SEVIS) from total international degrees completed, reported in NCSES data.

[18] We provide results of master's students separated by American and other international students in Figure A9.

We present the results in Figure A10. There are no meaningful effects prior to the reform year of 2003 (four years after the college expansion in 1999). This suggests that the treatment variable does not affect outcomes in the years prior to the reform. The positive effects on master's students emerge after 2006, with effect sizes increasing steadily through 2015. We do not detect meaningful effects on doctoral students.

5.4 Master's Programs and Tuition Revenues

To better understand the crowding-in documented above, we first examine the expansion in the number of master's programs. In addition, cross-subsidization may provide another channel: universities use tuition revenues from Chinese students to support the enrollment of other students (Shih, 2017; Bound et al., 2020). We investigate this possibility by looking at tuition revenues.

Master's Program Expansion. During our study period, US universities experienced rapid growth in master's programs. Between 2003 and 2013, the number of STEM master's programs increased by 23%, from 7,466 to 9,143, while the number of non-STEM master's programs grew by 16%, from 10,169 to 11,753.

Panel A of Table 4 reports results using the number of master's programs as the outcome. Both the OLS and IV specifications yield estimated coefficients around 1,[19] indicating that an additional 100 Chinese master's students was associated with the introduction of one new graduate program. A back-of-the-envelope calculation suggests that China's college expansion accounts for roughly 15% of the overall growth in US master's programs. By contrast, we find no effects on undergraduate or doctoral programs.

Panel B presents a heterogeneity analysis by field, distinguishing STEM from non-STEM programs. Using the same IV specification, we find that the growth in master's programs is concentrated in STEM fields. This result is consistent with our earlier findings: China's college expansion spurred more Chinese students to pursue STEM degrees in the United States, which in turn encouraged universities to expand STEM master's offerings and facilitated the crowding-in of additional STEM master's students.

Tuition Revenues. Cross-subsidization may be an important mechanism underlying American students' observed increase in degrees. Chinese students pay full fare, and are very likely to be self-funded (Bound et al., 2020). This revenue helps subsidize local students, and other university endeavors. In Table 5, we show that a 100-student increase in the supply of Chinese master's students is associated with a 3.4% increase in total tuition revenue and a 5.9% increase in core

[19] Standard errors from the shifter-level regression are reported in Table A15.

revenue.[20] However, this effect disappears when we examine tuition revenue per full-time student, suggesting that the additional revenue may be spent in a budget-neutral fashion on other students. This finding supports the notion of cross-subsidization across students. Moreover, we find no significant effects on tuition prices, further reinforcing the interpretation that increased demand from China did not cause US colleges to raise prices.

6 Effects on College Town Economies

We further investigate whether Chinese master's students generate spillover effects on the local economy. An increase in the number of Chinese students residing in a county can raise demand for local goods and services, thereby stimulating economic activity. To analyze these effects, we aggregate the data to the county-year level and examine local economic outcomes collected from the BDS. The empirical strategy follows the specification outlined in Section 5.1.

We report the first-stage estimates in Table A16. Columns (1)–(4) sequentially add controls: beginning with a baseline specification without controls, then including major-year fixed effects, province-year controls, and finally province–year fixed effects. We split the sample based on whether counties contain any "college towns," defined as having students comprise at least 20% of the population. As expected, the college-town sample yields strong first-stage F-statistics across all specifications, whereas the non-college-town sample shows substantially weaker instrument strength. This motivates our focus on the college-town sample for the main analysis.

Table 6 presents the estimated effects of Chinese master's students on local labor market outcomes in college towns. Overall, the results indicate that increases in Chinese student enrollment raise job creation, reduce job destruction, and thereby increase net job growth.

Panel A focuses on the service sector, and our OLS estimates document higher job creation, and lower job destruction rates. Our IV estimate is only precisely estimated for job destruction, with an estimate of –1.092, implying that 100 additional Chinese master's students in a college town are associated with a 1.09 percentage point decline in the job destruction rate. To gauge magnitude, the mean number of Chinese master's students in college towns is 26 (SD = 123), as shown in Table A1. Thus, a one-standard-deviation increase in Chinese master's students corresponds to a 1.343 percentage points reduction in job destruction rates.

In Panel B, we examine the goods sector, and find a positive effect on job creation. The IV estimate for job creation is 0.619, implying that a one-standard-deviation increase in Chinese master's students corresponds to a 0.76 percentage point increase in job creation.

In Panel C, we combine the service and goods sectors in college towns. We find a precise reduction in job destruction and a corresponding rise in net job creation. The IV estimate for

[20] Tuition revenue is core revenue multiplied by the tuition share in IPEDS. It has more missing values.

net job creation is 0.707, implying that 100 additional Chinese master's students raise the net job creation rate by 0.707 percentage points. Or a one-standard-deviation increase in Chinese master's students corresponds to a 0.869 percentage point rise in net job creation.

Overall, these results suggest that the impact of Chinese students extends beyond universities: while they reinforce the high-skilled education sector, they also stimulate employment in other parts of the local economy through increased demand for everyday goods and services.

7 Conclusion

While Chinese international students are part of the broader global flow of students, their sheer scale (partly driven by the dramatic expansion of China's higher education system beginning in 1999) and their concentration in STEM fields make them uniquely consequential for cross-border educational and economic outcomes. Identifying these effects is challenging, but in this study, we overcome several of these hurdles and document three key findings. First, China's college expansion substantially increased the number of Chinese graduate students studying in the United States. Second, this inflow had broad implications for the US higher education landscape, fueling the growth of STEM master's programs, attracting additional international and domestic students. And third, the influx of Chinese students and its spillovers stimulate the local economy surrounding college towns.

These results highlight just a few dimensions of the far-reaching impact of education reforms in countries with a large student population, such as China. Many downstream outcomes, such as the effects on research productivity, high-skilled labor supply, and technological innovation, remain important avenues for future work as suitable data and research designs become available.

Against this backdrop, recent policy shifts tightening student visa approvals, barriers to work visas, funding cuts for universities, increased scrutiny of Chinese applicants, and restricting participation in certain fields create challenges for US higher education, and the US economy. Our findings suggest that such restrictions would not only reduce the number of Chinese students themselves, but also dampen the crowding-in effects they generate for other international, and American students, further hurting college town economies.

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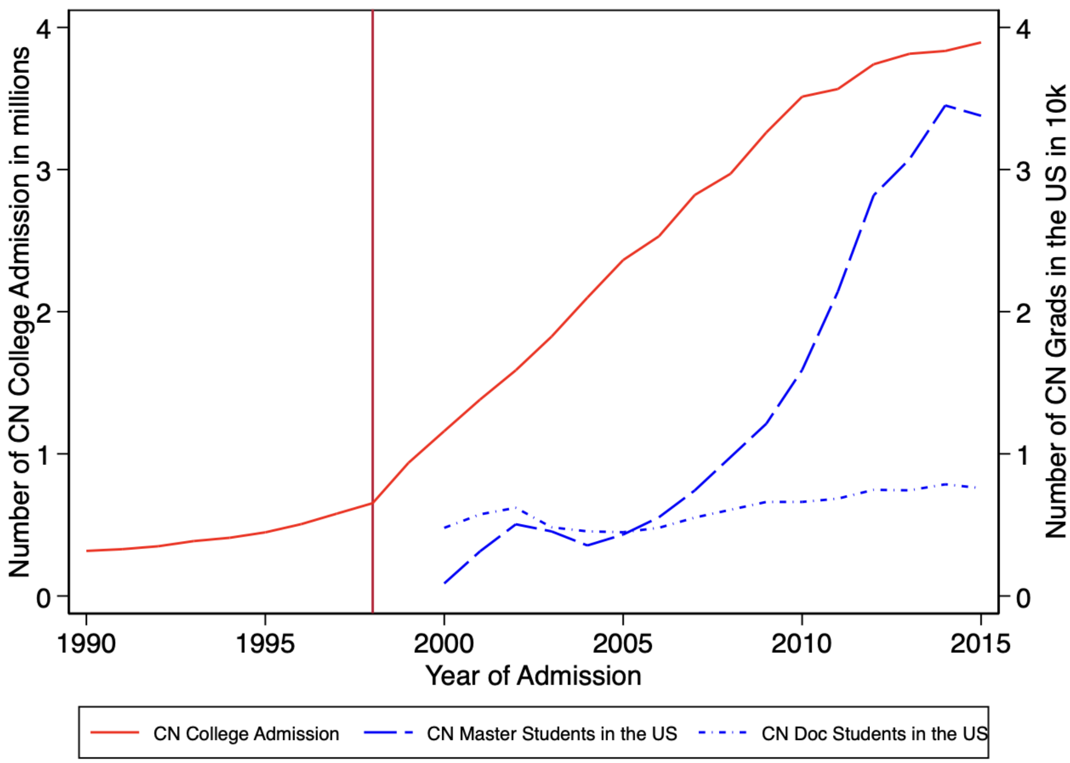
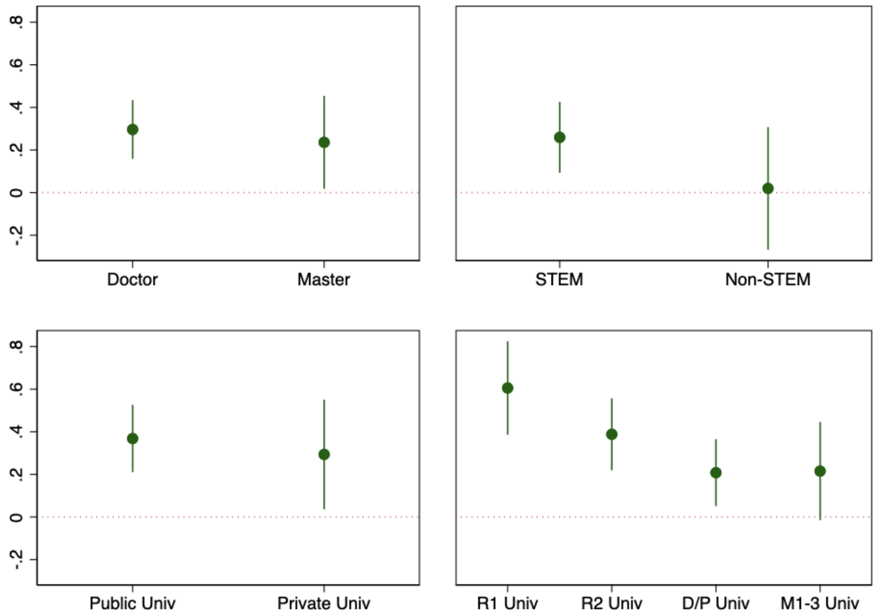
Figures

Figure 1: Trends in Chinese College Admissions and Chinese Students Studying in the US



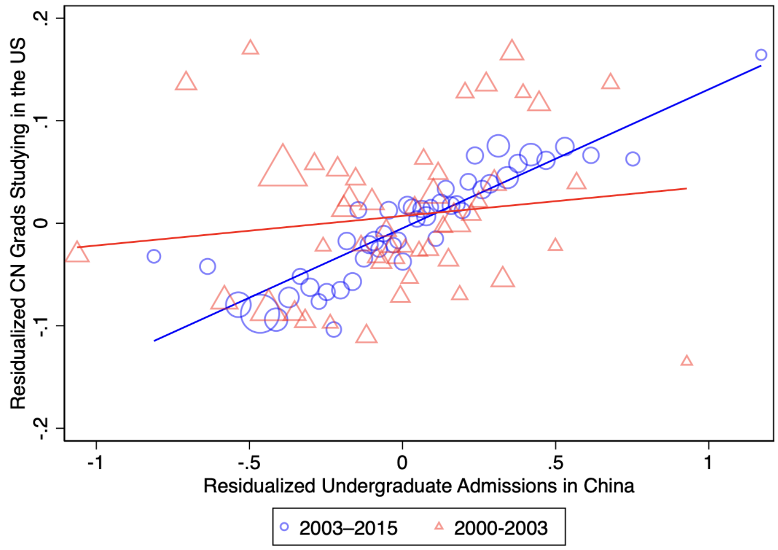
Notes: We plot the trends in Chinese college admissions (4-year college) and Chinese graduate admissions by US universities in the graph. The Chinese college admissions data comes from the China Education Statistical Yearbooks, and the US admissions data comes from the SEVIS database. We mark a vertical line in 1999, when China's college expansion officially started.

Figure 2: Heterogeneous Elasticity Between China's College Admissions and Chinese Grads to the US

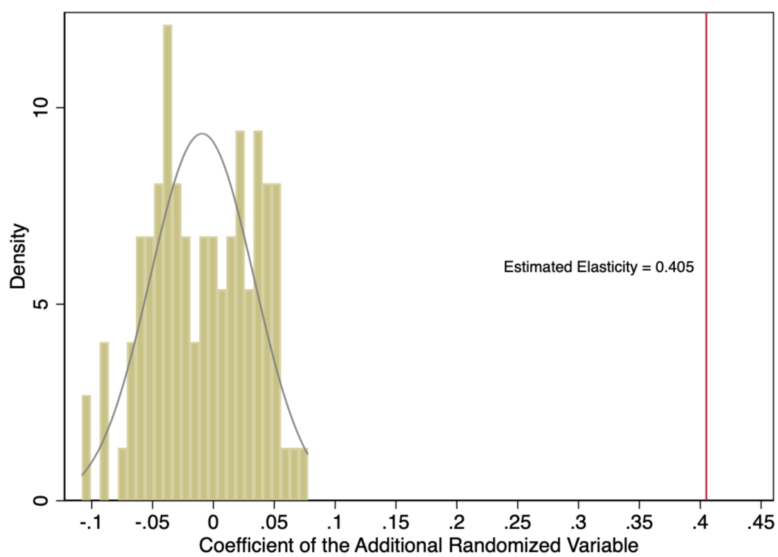


Notes: We analyze heterogeneity using the IV approach, with $Quota_{pmy} \times Share_{cm}$ as the instrument for Chinese college admissions. The coefficients represent the elasticity estimated by students' degree, major, and university type. For students' degrees and university types, we replace the aggregate outcome variable with the number of students studying for the particular degrees or in the specific universities. For students' majors, we split the samples so that we only target specific majors, i.e., STEM and non-STEM.

Figure 3: Effects of Chinese College Admissions on Chinese Grads to the US



(a) Residualzied Long-difference Correlation

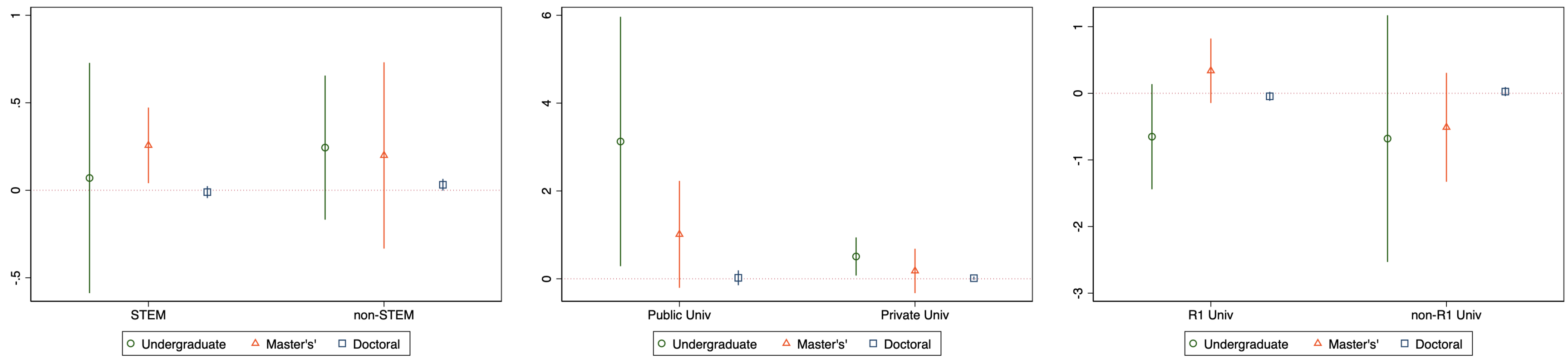


(b) Distribution of the Coefficient by Randomizing Cities of Origin

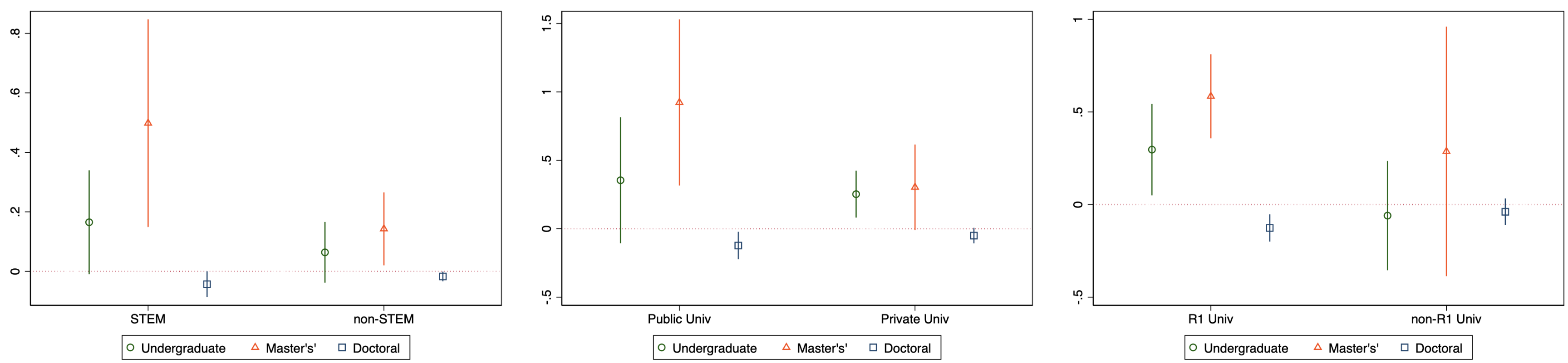
Notes: We use the merged data of college admissions and the SEVIS database. In Panel A, we plot the log-log relationship between China's college admissions of Chinese graduate students to the US. For the pre-reform period, due to the absence of college admissions data, we randomly assign each observation from 2000–2003 to a year between 2012 and 2015—the final three years of the post-reform period—while keeping the city and major fixed. We residualize the fixed effect of city-year and major-year and plot the scatter with 50 bins. The dot size represents the number of Chinese graduate students in the US in 2000. In Panel B, we apply a Poisson regression. The outcome variable is the Chinese graduate students admitted to the US. The independent variables are the original Chinese college admission number, with a placebo variable for which we randomly change the city of origin. City-year and major-year FEs are added. We run the regressions 100 times and plot the distribution in the plot. We mark the coefficient 0.405, which is the main result derived from the baseline model.

Figure 4: Heterogeneity in Impacts on Other Students in US Universities

Panel A: Effects on American Students

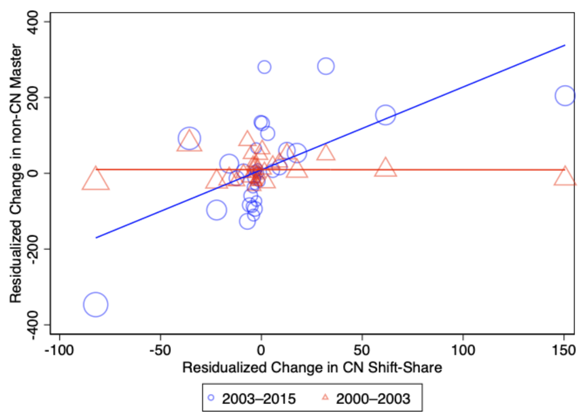


Panel B: Effects on Other International Students

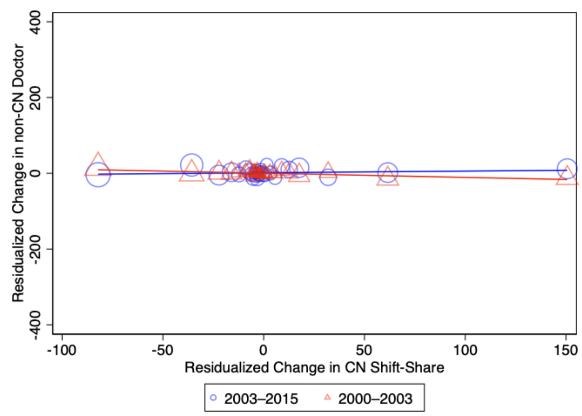


Notes: This figure presents heterogeneity analyses using the specification in Equation (4), instrumented by the shift-share defined in Equation (5). We also control for the province-year and major-year indicators in the model. We explore heterogeneity by students' major and university type. Panel A shows the effects on American students. Panel B shows the same analyses for other international students.

Figure 5: Correlation between Shift-Share and Year-on-Year Change in non-Chinese Enrollment



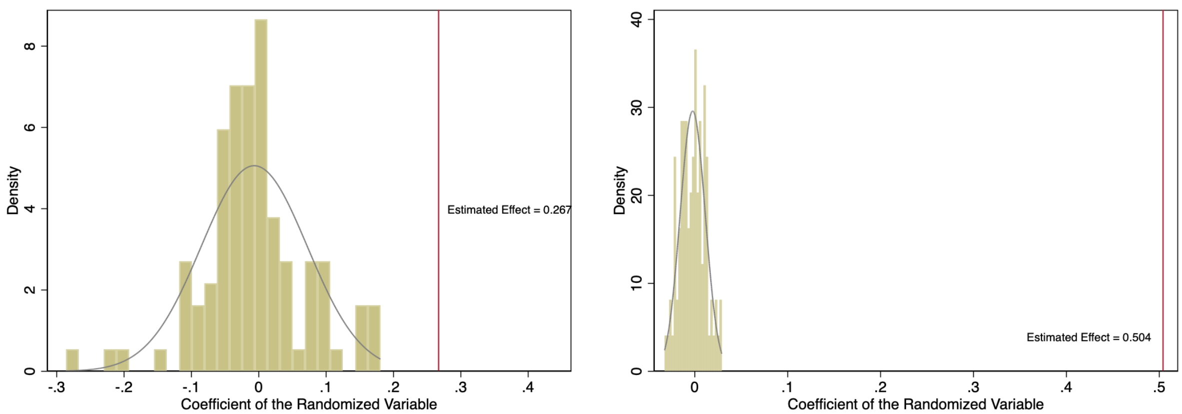
(a) non-Chinese Master's Students



(b) non-Chinese Doctoral Students

Notes: This figure presents the relationship between the long difference of non-Chinese students (including American and other international students) and the Chinese shift-share variable as defined in Equation (6). The unit of observation is university level. The outcome variables use the difference between 2003-2015 (pre-reform period) and 2000-2003 (post-reform period), and the independent variable is between 2003-2015. We present the residualized change after controlling for the province and major indicators, and the sum of shares in the model. We create 50 bins, and the dot size represents the number of all students in 2000. American students' data is from NSCES. International students' data is from the SEVIS.

Figure 6: Placebo Tests: Effects on American and Other International Master's Students



(a) American Master's Students

(b) Other International Master's Students

Notes: This figure presents placebo tests by randomly reassigning the outcome variable using another university's data in the same year. We use the specification in Equation (4), instrumented by the shift-share defined in Equation (5). We also control for the province-year and major-year indicators in the model. We perform this test for both American and other international master's students 100 times and present the distribution. We mark the coefficients derived from the baseline model.

Tables

Table 1: Chinese College Expansion and Chinese Graduate Students to US

	Poisson	First-stage		Reduced-Form Poisson		IV Poisson	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Chinese Grad	log(CollegeAdmit)	log(CollegeAdmit)	Chinese Grad	Chinese Grad	Chinese Grad	Chinese Grad
log(CollegeAdmit)	0.405^{***}					0.395^{***}	0.408^{***}
	(0.0437)					(0.0757)	(0.0998)
Quota × Share		1.580^{***}	1.058^{***}	0.256^{**}	0.329^{***}		
		(0.196)	(0.120)	(0.119)	(0.105)		
Quota			0.297^{***}		0.154^{***}		0.0693^{**}
			(0.0191)		(0.0313)		(0.0349)
Share			0.923^{***}		0.511^{*}		0.461^{*}
			(0.137)		(0.296)		(0.257)
Observations	56820	56820	56820	63765	63765	56820	56820
Mean	5.468	4.924	4.924	5.511	5.511	5.473	5.473
F-stats		64.87	77.26				
City-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
15 Major-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data sources are China College Admission Database and SEVIS database. Columns (4) and (5) have a larger number of observations due to fewer missing values. We apply the PPML model in columns (1), and (4)-(7). The dependent variable is *ChineseGrad*. The independent variable is *log(CollegeAdmit)*. We add one to the independent variable as 1% of the data is 0. We use $Quota \times Share$ as the shift-share instrument, where *Quota* is the admission quota for each province for each major in a certain year, in units of 10,000 students. *Share* is the city-major exposure to the provincial quota in 1999. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Chinese College Expansion and Chinese Graduate Students to US: Heterogeneity by Cities

	Dependent Variable: Number of Chinese Graduate Students in the US		
	Samples w/o Beijing & Shanghai	Big Cities	Small Cities
	(1)	(2)	(3)
log(CollegeAdmit)	0.440^{***}	0.457^{***}	0.335^{***}
	(0.0807)	(0.119)	(0.0850)
Quota	0.00811	0.0590	0.0328
	(0.0223)	(0.0374)	(0.0304)
Share	0.569^{**}	0.402	0.347
	(0.246)	(0.305)	(0.375)
Observations	56820	56820	56820
Mean	3.686	15.53	1.396
R^2	0.860	0.944	0.673
City-Year FE	Yes	Yes	Yes
15 Major-Year FE	Yes	Yes	Yes

Notes: Data sources are China College Admission Database and SEVIS database. We apply the PPML model. The dependent variable is *ChineseGrad*. The independent variable is *log(CollegeAdmit)*. We add one to the dependent variable as 1% of the data is 0. We use $Quota \times Share$ as the shift-share instrument, where *Quota* is the admission quota for each province for each major in a certain year. We multiple this variable by 10,000 to obtain a more comparable estimate. *Share* is the city-major exposure to the provincial quota in 1999. Big cities are those with more than 5 million population and vice versa for small cities. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Effects on Other Students by Level of Study

	OLS			IV w/ Shifter Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Undergraduate	Master's	Doctoral	Undergraduate	Master's	Doctoral
Panel A: American Students (NCSES Data)						
Chinese Masters	0.352**	0.441***	0.0158**	0.382	0.264	0.00378
	(0.153)	(0.165)	(0.00760)	(0.564)	(0.330)	(0.0265)
Observations	13828	13828	13828	13828	13828	13828
Mean	1142.8	420.6	34.73	1142.8	420.6	34.73
F-stats				32.91	32.91	32.91
Panel B: Other International Students (SEVIS Data)						
Chinese Masters	0.0852***	0.180***	-0.0194**	0.266**	0.504**	-0.0895***
	(0.0300)	(0.0441)	(0.00796)	(0.127)	(0.204)	(0.0322)
Observations	13413	13413	13413	13413	13413	13413
Mean	44.66	49.69	12.85	44.66	49.69	12.85
F-stats				32.66	32.66	32.66
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
4 Major-Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data on Chinese and other international students come from the SEVIS database, while data on American students are sourced from the NCSES database. The NCSES data do not provide information on student enrollment, but only on degrees completed by level of study. In the analysis, we proxy enrollment at each level using degree completions observed a few years later, assuming four years for undergraduate programs, two years for master's programs, and five years for doctoral programs. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). We provide the corresponding first-stage F-stats in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effects on Number of Programs Offered by US Universities

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			IV w/ Shifter Controls		
	Undergraduate	Master's	Doctoral	Undergraduate	Master's	Doctoral
Panel A: Number of All the Programs						
Chinese Masters×100	0.168	1.108***	0.292***	0.289	0.985**	-0.0146
	(0.135)	(0.195)	(0.0959)	(0.573)	(0.496)	(0.374)
Observations	13737	13737	13737	13737	13737	13737
Mean	31.58	18.46	7.514	31.58	18.46	7.514
F-stats				36.04	36.04	36.04
Panel B: Heterogeneous Effect by STEM (using the IV specification)						
	Bachelor		Master		Doctor	
	STEM	non-STEM	STEM	non-STEM	STEM	non-STEM
Chinese Masters×100	-0.0737	0.360	0.770**	0.00197	0.283	-0.264
	(0.320)	(0.366)	(0.316)	(0.273)	(0.268)	(0.208)
Observations	13737	13737	13737	13737	13737	13737
Mean	12.20	19.09	7.806	10.45	4.451	2.937
F-stats	36.04	36.04	36.04	36.04	36.04	36.04
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
4 Major-Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data on Chinese and other international students come from the SEVIS database, while data on all the programs are sourced from the NCSES database. We infer the number of programs from the unique major within each university-year using the 4-digit Classification of Instructional Programs (CIP) code. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). We provide the corresponding first-stage F-stats in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effects on Tuition Revenue and Price

	OLS			IV w/ Shifter Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: log(Tuition Revenue)						
	Tuition Rev	Core Rev	Tuition Rev/FTE	Tuition Rev	Core Rev	Tuition Rev/FTE
Chinese Master×100	0.0277***	0.0200***	0.0173***	0.0338	0.0593**	-0.0190
	(0.00669)	(0.00492)	(0.00509)	(0.0211)	(0.0294)	(0.0208)
Observations	11328	12327	10381	11328	12327	10381
Mean	17.55	18.33	9.254	17.55	18.33	9.254
F-stats				32.91	36.47	26.66
Panel B: log(Tuition Price)						
	District	in-State	out-of-State	District	in-State	out-of-State
Chinese Master×100	-0.00211	-0.00218	-0.00291	0.00775	0.00643	-0.00478
	(0.00583)	(0.00581)	(0.00549)	(0.0201)	(0.0198)	(0.0199)
Observations	12114	12115	12116	12114	12115	12116
Mean	9.303	9.303	9.604	9.303	9.303	9.604
F-stats				35.99	35.99	35.99
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
4 Major-Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data on Chinese students come from the SEVIS database. Data on revenue comes from IPEDS. Tuition revenue is imputed by multiplying core revenue by the tuition share reported in IPEDS, thus it has more missing values. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). We provide the corresponding first-stage F-stats in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

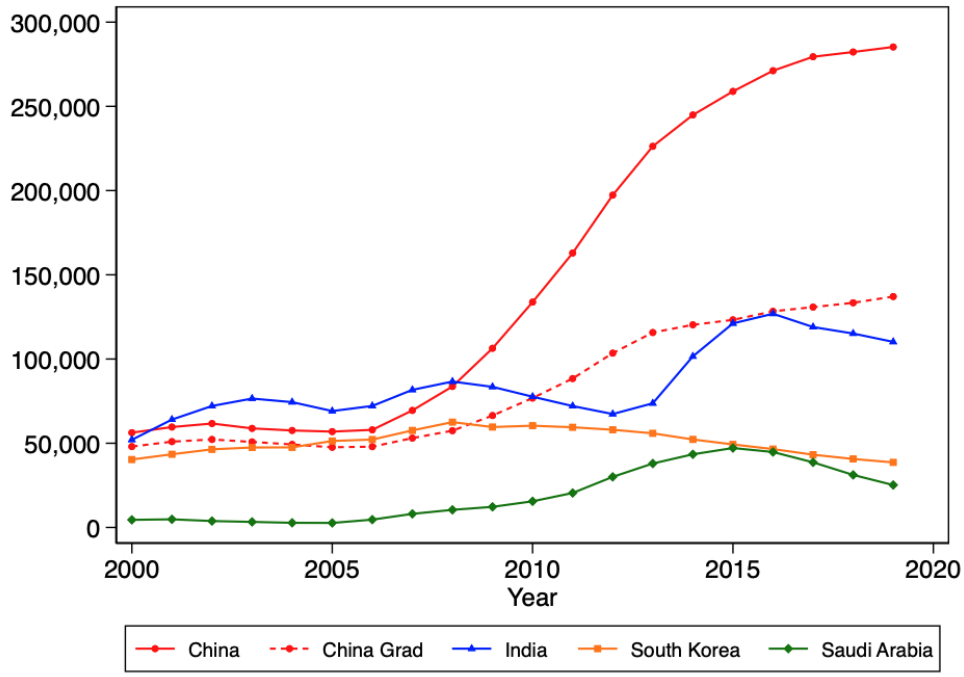
Table 6: Effects on Job Creation/Destruction Rate in College Town Counties

	OLS			IV w/ Shifter Controls		
	(1)	(2)	(3)	(4)	(5)	(6)
	Creation	Destruction	Net Creation	Creation	Destruction	Net Creation
Panel A: Service Sector						
Chinese Master$\times$100	0.0903***	-0.0809**	0.171***	-0.405	-1.092**	0.687
	(0.0283)	(0.0356)	(0.0558)	(0.388)	(0.428)	(0.569)
Observations	5525	5525	5525	5525	5525	5525
Mean	15.50	14.79	0.718	15.50	14.79	0.718
F-stats				51.70	51.70	51.70
Panel B: Goods Sector						
Chinese Master$\times$100	0.0611**	-0.0724*	0.133**	0.619*	0.433	0.180
	(0.0254)	(0.0416)	(0.0534)	(0.316)	(0.454)	(0.542)
Observations	5525	5525	5525	5525	5525	5525
Mean	8.450	8.375	0.0736	8.450	8.375	0.0736
F-stats				51.70	51.70	51.70
Panel C: Both Sectors						
Chinese Master$\times$100	0.0730***	-0.0396*	0.113***	0.00522	-0.702***	0.707*
	(0.0186)	(0.0222)	(0.0338)	(0.230)	(0.268)	(0.363)
Observations	5525	5525	5525	5525	5525	5525
Mean	12.63	12.02	0.607	12.63	12.02	0.607
F-stats				51.70	51.70	51.70
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data source is from the SEVIS database and the Business Dynamics Statistics (BDS). All outcomes are measured as rates ($\times$100) relative to the previous year's total employment. A college town is a city or town where a university significantly influences the local economy and culture, often with students making up at least 20% of the population. The university may be the largest employer, and many businesses cater primarily to students. We select the American college towns following the definition on Wikipedia. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

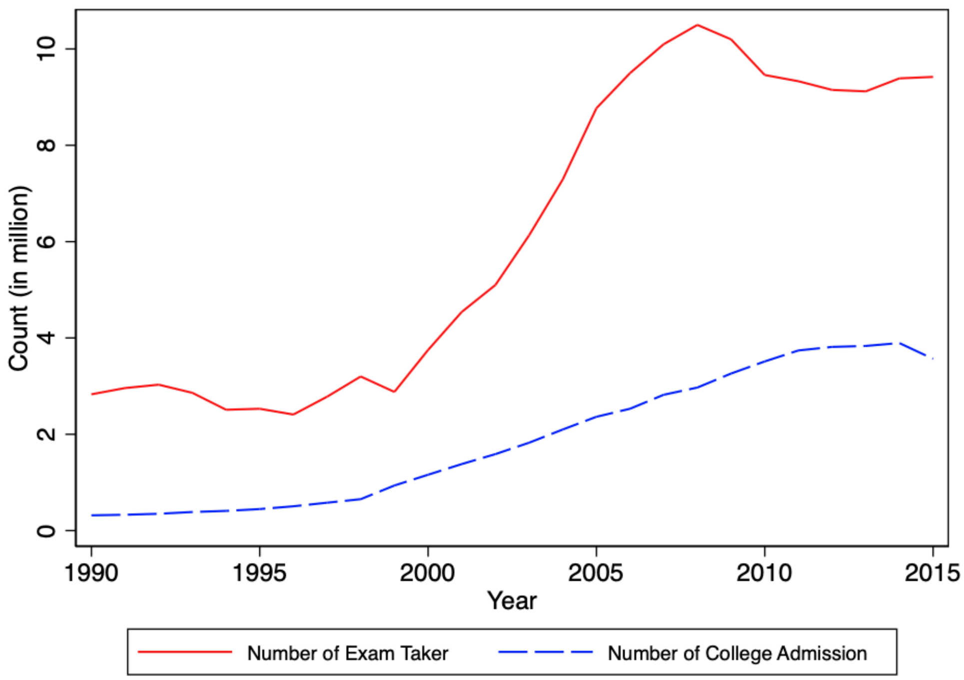
Online Appendix

Figure A1: Trends For Four Countries of Origin



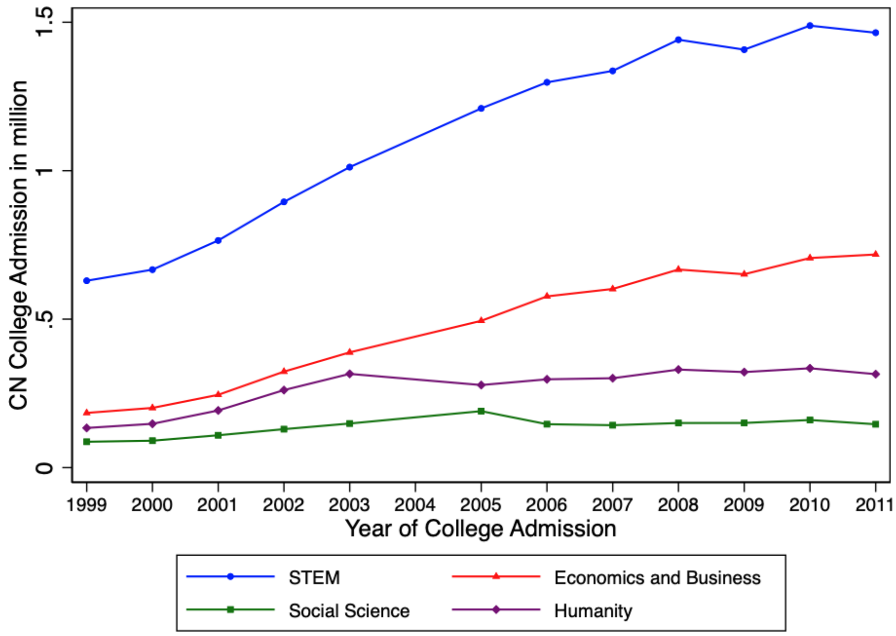
Notes: Data on enrollment by country of origin comes from Open Doors, Institute for International Education, 2000-2020. We show the top four countries of origin for international students studying in the US. We distinguish graduate students from China, while for other countries, the data combine graduate and undergraduate students. Degree-specific data prior to 2000 are not available.

Figure A2: Trends in Chinese College Exam Takers and Admissions

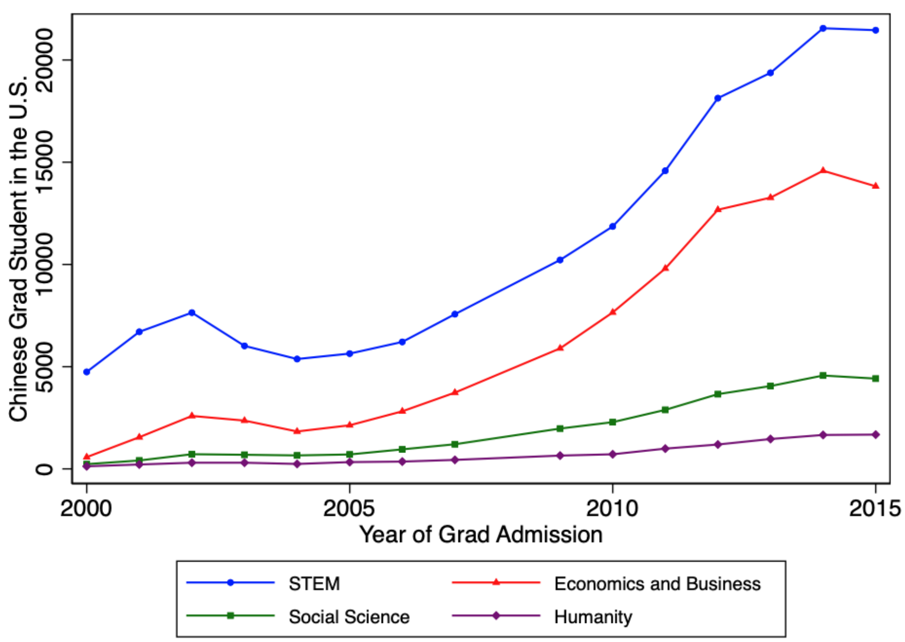


Notes: Data comes from the China Education Statistical Yearbooks. The college admission number only includes 4-year colleges, which accounts for approximately 40% of total higher-education enrollment. Despite the college expansion, the quotas were always binding: many more students took part in the college entrance exam than the quota.

Figure A3: Students Admissions by Major



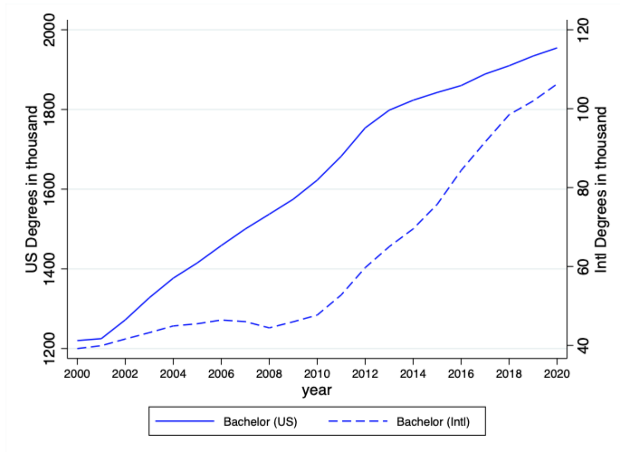
(a) Chinese College Undergraduate Admissions



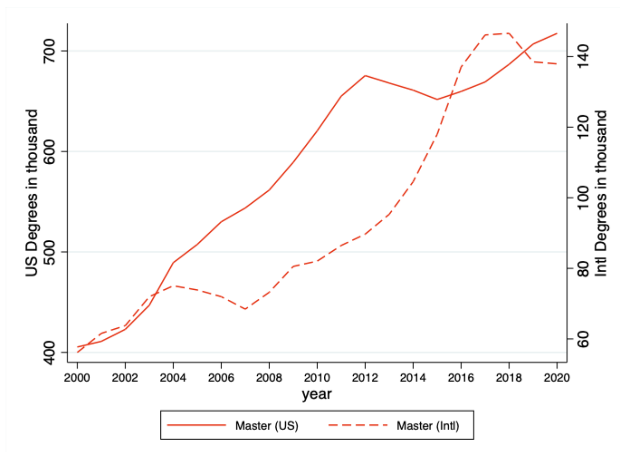
(b) American Graduate School Admission

Notes: We plot the trends in Chinese college admissions (4-year colleges) and the Chinese graduate student admissions by American universities for four majors in the graph. The Chinese admission data comes from the college admission administrative database, and the American admission data comes from the SEVIS database.

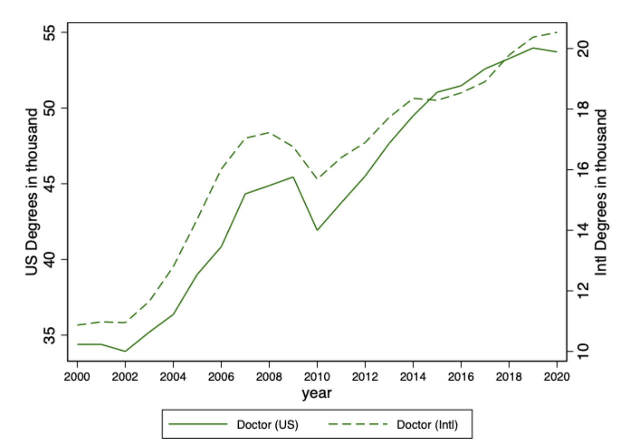
Figure A4: Trends in Completed Degrees in the US



(a) Bachelor’s



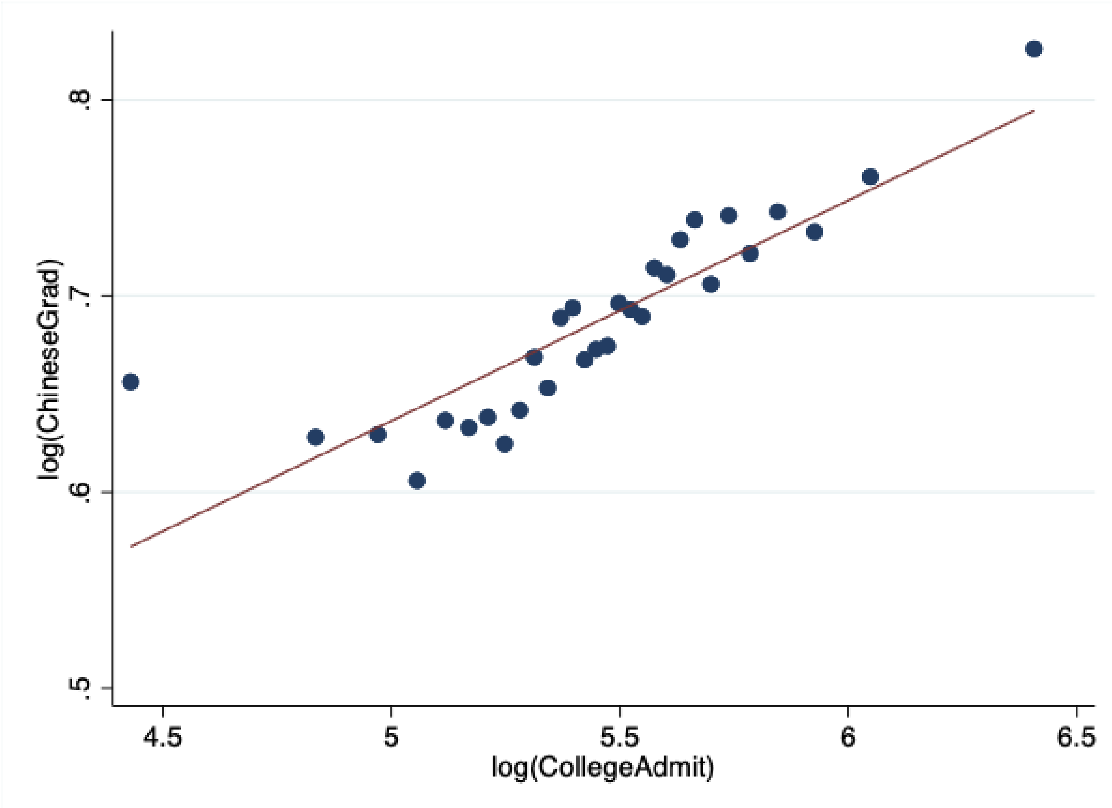
(b) Master’s



(c) Doctorate

Notes: The data source is the National Center for Science and Engineering Statistics (NCSES) provided by NSF. There was a definition change regarding doctorate degrees around 2008, resulting in a temporary drop in numbers.

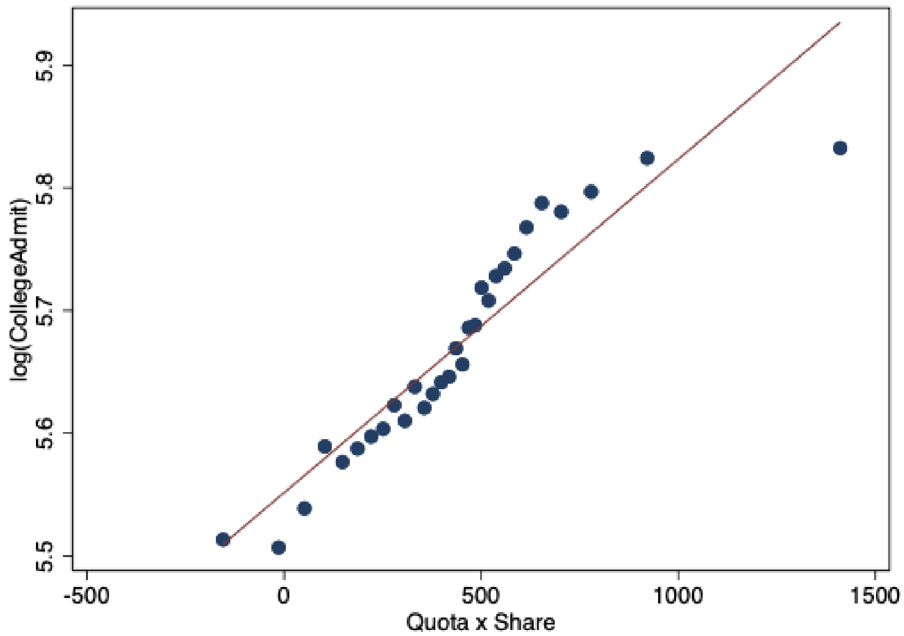
Figure A5: Residualized Plot for the OLS Approach



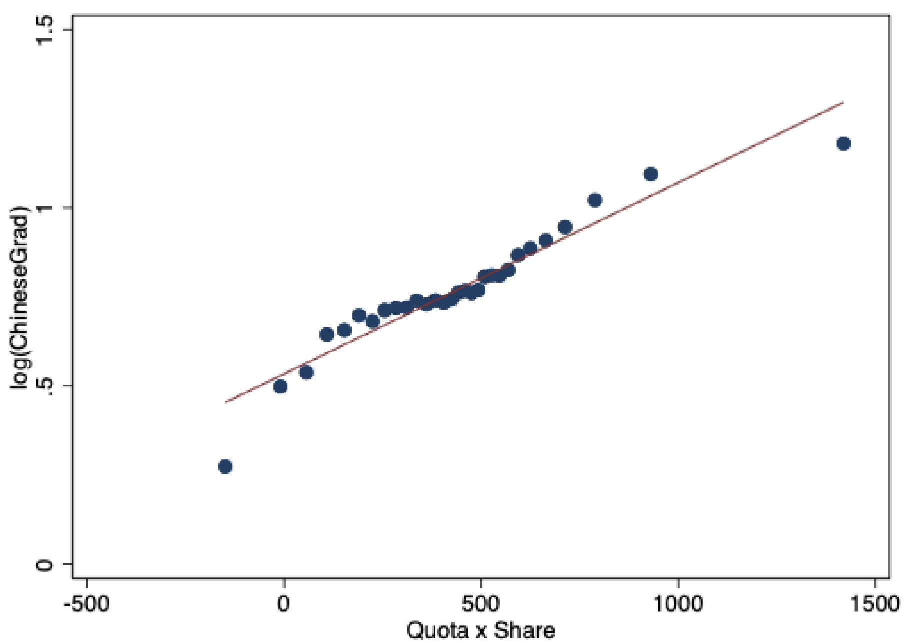
Notes: We plot the binscatter relationship for *log(ChineseGrad)* and *log(CollegeAdmission)*. Since all the variables contain zeros, we use the inverse hyperbolic sine to replace the log. We absorb city-year and major-year FEs. We truncate the 2% observations at both left and right tails.

Figure A6: Residualized Plot for the IV Approach

(a) First Stage

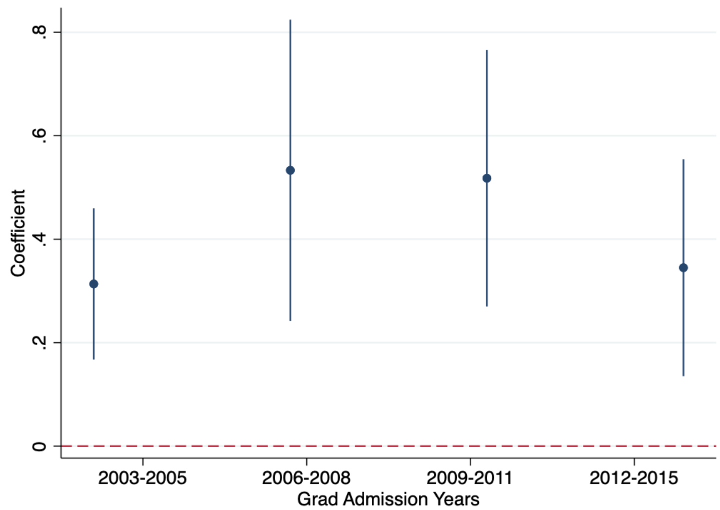


(b) Reduced Form

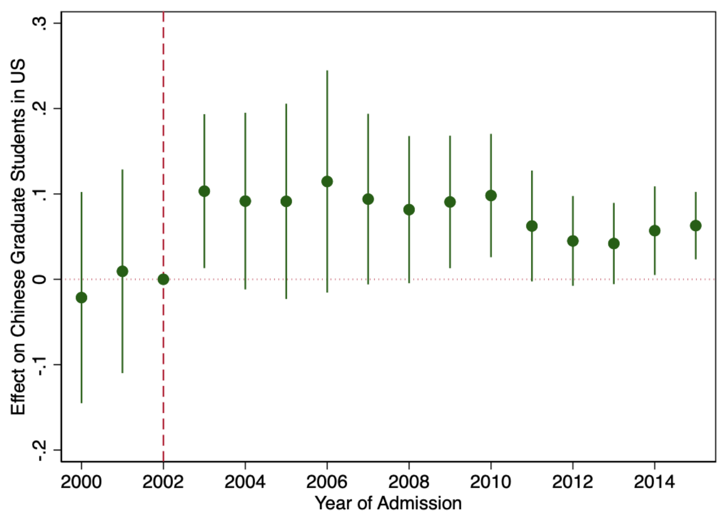


Notes: We plot the binscatter relationship for *log(ChineseGrad)* and $log(Quata \times Share)$ and textitlog(CollegeAdmission) and $log(Quata \times Share)$. Since both the variables contain zeros, we use the inverse hyperbolic sine to replace the log. We absorb city-year and major-year FEs. We truncate the 2% observations at both left and right tails.

Figure A7: Dynamic Effects of Chinese College Admissions on Chinese Graduate Students in the US



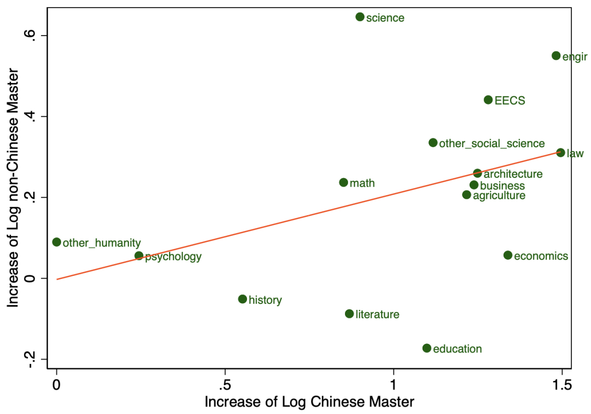
(a) Elasticity by Years



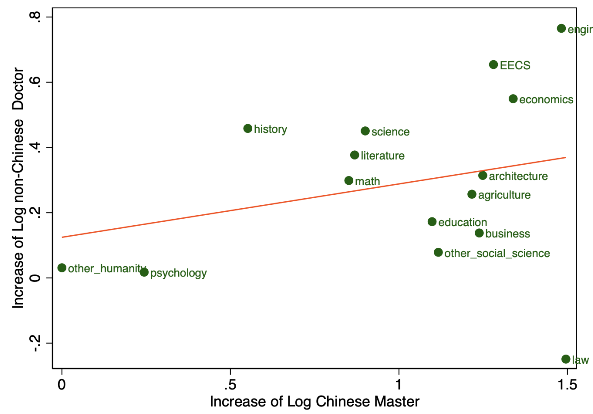
(b) Event Study Results

Notes: Data sources are China College Admission Database and SEVIS database. We apply the PPML model. The dependent variable is *ChineseGrad*. The independent variable is *log(CollegeAdmit)*. We add one to the independent variable as 1% of the data is 0. We use *Quota* $\times$ *Share* as the shift-share instrument, where *Quota* is the admission quota for each province for each major in a certain year. *Share* is the city-major exposure to the provincial quota in 1999. We provide the 95% confidence interval in the figure.

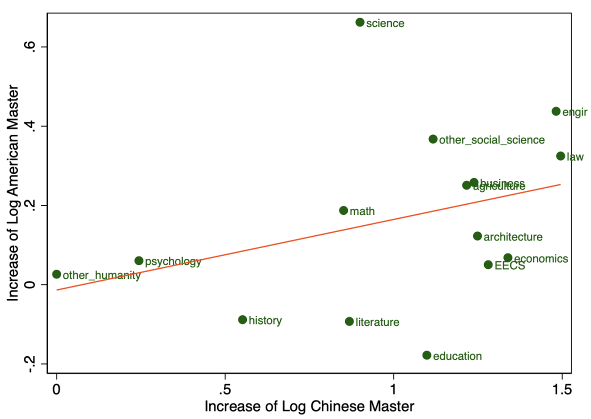
Figure A8: Long-diff Correlation between Chinese Master's Students and non-Chinese Students by Major



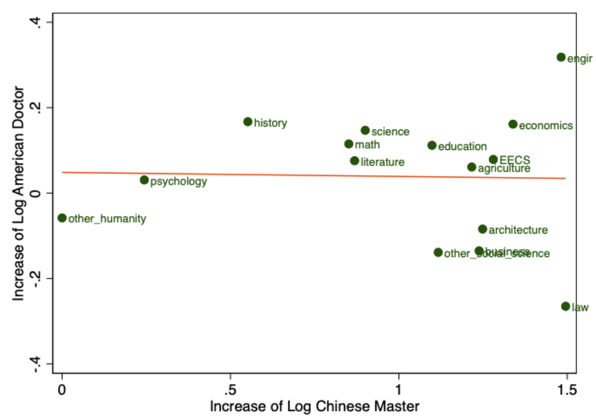
(a) non-Chinese Master's Students



(b) non-Chinese Doctorate Students



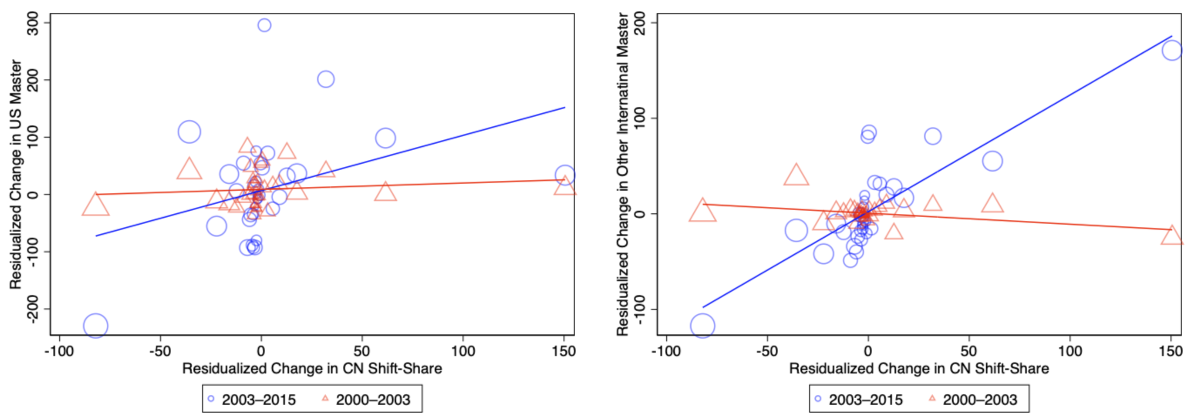
(c) American Master's Students



(d) American Doctorate Students

Notes: We plot the log change of the student numbers by major between 2004 and 2015. We take the average of the change of each variable across each university for each major. American students' data is from NSCES. International students' data is from the SEVIS.

Figure A9: Correlation between Shift-Share and Year-on-Year Change in non-Chinese Enrollment

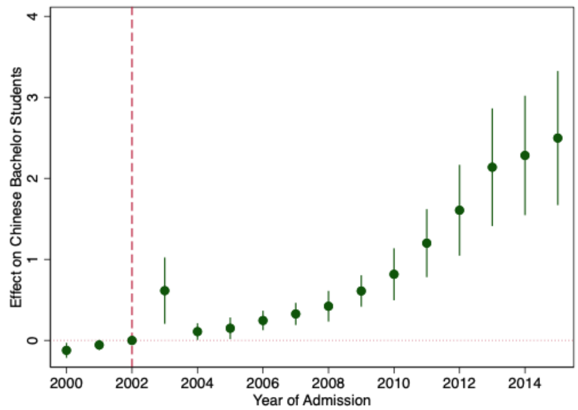


(a) American Master's Students

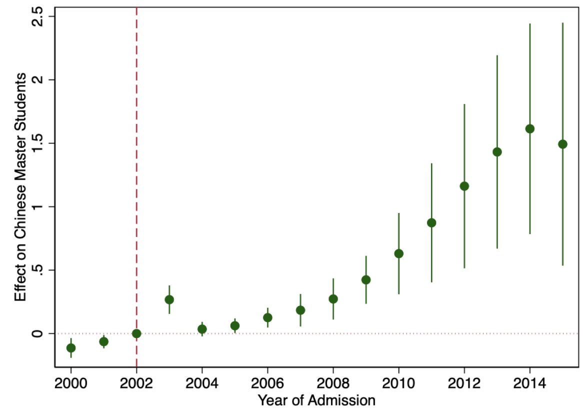
(b) Other International Master's Students

Notes: This figure presents the relationship between the long difference of US/other international students and the Chinese shift-share variable as defined in Equation (6). The outcome variables use the difference between 2003-2015 and 2000-2003, and the independent variable is between 2003-2015. The unit of observation is the university. After controlling for the province and major indicators, we present the residualized change and the sum of shares in the model. We create 50 bins, and the dot size represents the number of all students in 2000. American students' data is from NSCES and spans 1995 to 2015. International students' data is from the SEVIS and spans 2000 to 2015.

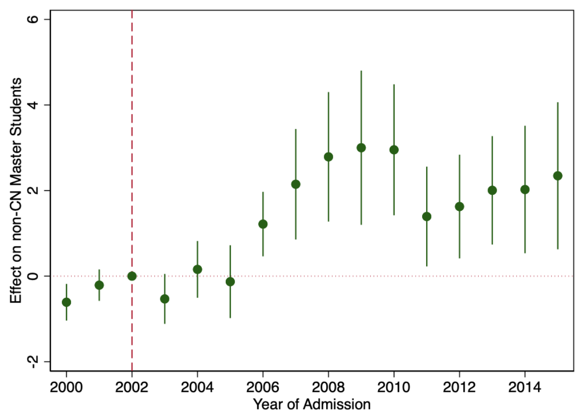
Figure A10: Event Study Figures for Other Student Enrollment



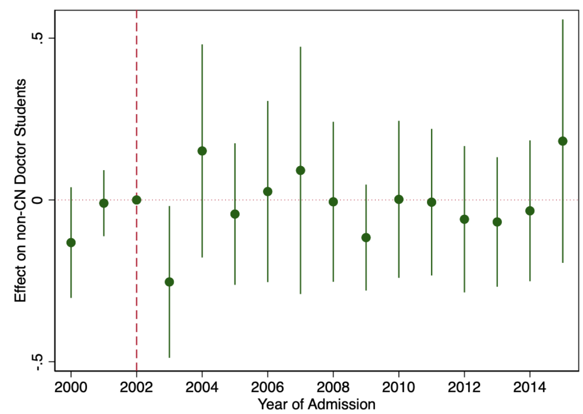
(a) All Chinese Students



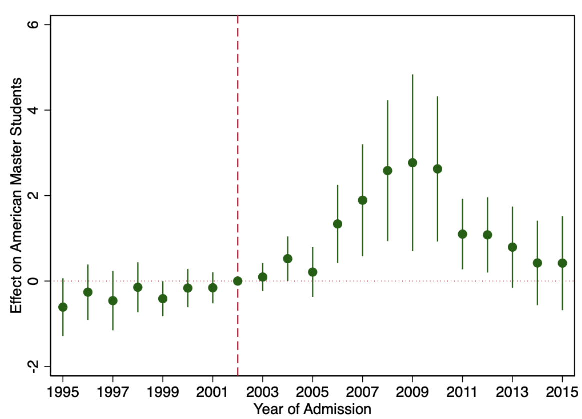
(b) Chinese Master's Students



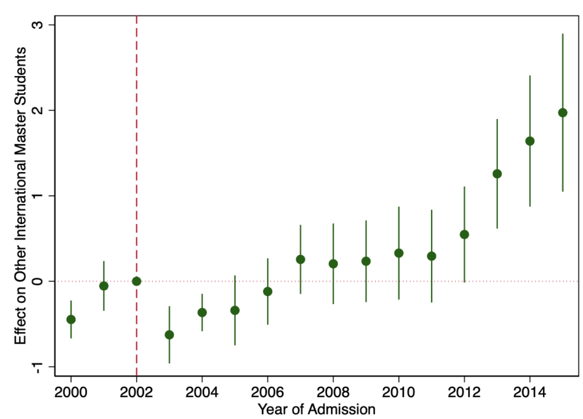
(c) non-Chinese Master's Students



(d) non-Chinese Doctoral Students



(e) American Master's Students



(f) Other International Master's Students

Notes: This figure presents the event study results for other students' enrollment. The treatment variable is the long-difference of the shift-share variable as defined in Equation (5) between 2003 to 2008. We also control for the province-year, major-year indicators, and the sum of shares in the model. American students' data is from NSCES and spans 1995 to 2015. International students' data is from the SEVIS and spans 2000 to 2015.

Table A1: Summary Statistics

	N	Zero	ZeroPct	Mean	SD	Min	Max
Panel A: At the Chinese city-major-year level							
Chinese College Admission	56820	872	0.02	426.255	727.068	0	16106
Chinese Graduate Students	63765	37621	0.59	4.867	39.335	0	2822
Chinese Master's Students	63765	42875	0.67	3.531	34.617	0	2746
Chinese Doctoral Students	63765	47556	0.75	1.335	9.174	0	451
Chinese Graduate Students in Public Univ	63765	42423	0.67	2.529	17.249	0	1053
Chinese Graduate Students in Private Univ	63765	46090	0.72	2.337	22.808	0	1837
Chinese Graduate Students in R1 Univ	63765	42706	0.67	2.706	20.993	0	1456
Chinese Graduate Students in R2 Univ	63765	52529	0.82	0.818	6.876	0	522
Chinese Graduate Students in D/P Univ	63765	58733	0.92	0.273	3.625	0	340
Chinese Graduate Students in Master Univ	63765	55312	0.87	0.567	5.542	0	423
Panel B: At the US university-year level							
Chinese Graduate Students	14358	6360	0.44	19.996	72.272	0	1654
Chinese Master's Students	14358	6757	0.47	14.547	60.843	0	1544
Chinese Doctoral Students	14358	10729	0.75	5.449	17.278	0	207
Chinese Undergraduate Students	14358	11635	0.81	4.334	29.024	0	721
Chinese Graduate Students in STEM Majors	14358	9187	0.64	10.699	43.524	0	1036
Chinese Graduate Students in non-STEM Majors	14358	7503	0.52	9.297	34.638	0	704
Panel C: At the college-town county-year level							
Chinese Graduate Students	5525	2366	0.43	37.012	148.243	0	3151
Chinese Master	5525	2457	0.44	26.004	122.709	0	2684
Chinese Doctor	5525	3724	0.67	11.008	31.504	0	471

Notes: Data sources are China College Admission Database and SEVIS database. In Panel (A), the unit of observation is Chinese city-major-year. We have missing data from the China's college admission database, so the observation is smaller than others.

Table A2: Chinese College Expansion and F1 Graduate Students 03-15: Poisson Baseline

	Dependent Variable: Number of Chinese Graduate Students in the U.S.						
	Whole Sample				Samples w/o BJ&SH	Big Cities	Small Cities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(CollegeAdmit)	1.614^{***}	0.896^{***}	0.921^{***}	0.405^{***}	0.379^{***}	0.417^{***}	0.324^{***}
	(0.145)	(0.0186)	(0.0154)	(0.0437)	(0.0413)	(0.0576)	(0.0325)
Observations	56820	56820	56820	56820	56460	15015	15015
Mean	4.848	5.468	5.468	5.468	3.683	15.53	1.394
R^2	0.363	0.869	0.892	0.921	0.860	0.944	0.673
City-Year FE		Yes	Yes	Yes	Yes	Yes	Yes
4 Major-Year FE			Yes				
15 Major-Year FE				Yes	Yes	Yes	Yes

Notes: Data sourcess are China College Admission Database and SEVIS database. We apply the PPML model. The dependent variable is *ChineseGrad*, and the independent variable is *log(CollegeAdmit)*. We add one to the dependent variable as 1% of the data is 0. BJ stands for Beijing, and SH stands for Shanghai. Big cities are those with more than 5 million population and vice versa for small cities. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Chinese College Expansion and F1 Graduate Students 03-15: Level Results

	Dependent Variable: Number of Chinese Graduate Students in the US						
	Whole Sample				Samples w/o BJ&SH	Big Cities	Small Cities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
College Admit	0.0270***	0.0246***	0.0258***	0.0361***	0.0149***	0.0520**	0.00455***
	(0.00952)	(0.00842)	(0.00913)	(0.0134)	(0.00242)	(0.0212)	(0.000636)
Observations	56820	56820	56820	56820	56460	15015	15015
Mean	4.848	4.848	4.848	4.848	3.262	15.03	1.189
R^2	0.234	0.523	0.527	0.560	0.570	0.597	0.552
City-Year FE		Yes	Yes	Yes	Yes	Yes	Yes
4 Major-Year FE			Yes				
15 Major-Year FE				Yes	Yes	Yes	Yes

Notes: Data sources are China College Admission Database and SEVIS database. We apply the linear OLS model. The dependent variable is Chinese Grad, and the independent variable is College Admit. BJ stands for Beijing, and SH stands for Shanghai. Big cities are those with more than 5 million population and vice versa for small cities.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Chinese College Expansion and F1 Graduate Students 03-15: Poisson Baseline with province aggregated

	Dependent Variable: Number of Chinese Graduate Students in the US					
	Whole Sample				Samples w/o BJ&SH	Big Provinces
log(CollegeAdmit)	0.337***	0.904***	0.386***	0.414***	0.397***	0.418***
	(0.0405)	(0.0221)	(0.0596)	(0.0667)	(0.0958)	(0.0697)
Observations	5234	5234	5234	5234	4874	4170
Mean	53.24	53.24	53.24	53.24	38.45	65.14
R^2	0.943	0.849	0.945	0.953	0.934	0.952
ProvinceFE	Yes	No	No	No	No	No
MajorFE	Yes	No	Yes	No	No	No
YearFE	Yes	No	No	No	No	No
ProvYearFE	No	Yes	Yes	Yes	Yes	Yes
MajorYearFE	No	No	No	Yes	Yes	Yes

Notes: Data sources are China College Admission Database and SEVIS database. We apply the Poisson model as the baseline analysis. The dependent variable is *ChineseGrad* and the dependent variable is *CollegeAdmit*, both aggregated at the province level. We show the results using different sets of fixed effects and different samples in this table. The coefficient can be interpreted as the estimated elasticity. BJ stands for Beijing, and SH stands for Shanghai. Big provinces are those that contain cities with more than 5 million population.

Table A5: University-level First-Stage Results

Dep Var: Number of Chinese Master's Students in the US			
	(1)	(2)	(3)
Panel A: All Sample			
Shift-Share	1.634***	1.471***	1.505***
	(0.201)	(0.227)	(0.250)
Observations	14355	14355	14355
Mean	14.55	14.55	14.55
F-stats	66.05	41.84	36.20
Panel B: American Students' Sample			
Shift-Share	1.550***	1.503***	1.594***
	(0.211)	(0.226)	(0.278)
Observations	13828	13828	13828
Mean	13.37	13.37	13.37
F-stats	53.86	44.38	32.91
Panel C: Other International Students Sample			
Shift-Share	1.020***	0.942***	1.071***
	(0.107)	(0.115)	(0.187)
Observations	13413	13413	13413
Mean	12.11	12.11	12.11
F-stats	91.60	67.10	32.66
Year FE	Yes	Yes	Yes
University FE	Yes	Yes	Yes
Sum of Share		Yes	Yes
Province-Year Indicators			Yes
4 Major-Year Indicators			Yes

Notes: The data source is the SEVIS database. The Shift-Share instrument is created following Equation (5). We use three different samples in Panels A–C, as the samples used to examine the effects sightly differ due to missing data issues. The three samples correspond to analyses of other Chinese students, American students, and other international students. Standard errors are clustered at the university level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Shifter Level Regressions: Impacts on American Students

	(1) Homoskedasticity	(2) Heteroskedasticity	(3) Cluster on Province-Major	(4) Cluster on Province
Panel A: Results on Number of American Bachelor Degrees				
Chinese Masters	0.382	0.382	0.382	0.382
	(0.372)	(0.348)	(0.454)	(0.290)
Panel B: Results on Number of American Master's Degrees				
Chinese Masters	0.264	0.264	0.264	0.264
	(0.196)	(0.185)	(0.210)	(0.159)
Panel C: Results on Number of American Doctorate Degrees				
Chinese Masters	0.00378	0.00378	0.00378	0.00378
	(0.0261)	(0.0216)	(0.0168)	(0.0143)
Observations	3753	3753	3753	3753
Number of Cluster			119	30

Notes: Data on Chinese students come from the SEVIS database, while data on American students are sourced from the NCSES database. The NCSES data do not provide information on student enrollment, but only on degrees completed by level of study. In the analysis, we proxy enrollment at each level using degree completions observed a few years later, assuming four years for undergraduate programs, two years for master's programs, and five years for doctoral programs. The analysis is conducted at the shifter level, with exposure-robust standard errors computed following the method proposed by Borusyak et al. (2022). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Effects on American Bachelor's Degrees Obtained in 4 Years

	Dep Var: American Bachelor's Degrees Obtained in 4 Years			
	OLS	IV w/ Shifter Controls		
	(1)	(2)	(3)	(4)
Chinese Masters	0.352**	0.659**	0.920**	0.382
	(0.153)	(0.295)	(0.407)	(0.564)
Observations	13828	13828	13828	13828
Mean	1142.8	1142.8	1142.8	1142.8
F-stats		53.86	44.38	32.91
Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
Sum of Share			Yes	Yes
Province-Year Indicators				Yes
4 Major-Year Indicators				Yes

Notes: Data on American students are sourced from the NCSES database. These data do not provide information on student enrollment, but only on degrees completed by level of study. In the analysis, we proxy enrollment at each level using degree completions observed a few years later, assuming four years for undergraduate programs, two years for master's programs, and five years for doctoral programs. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). We provide the corresponding first-stage F-stats in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Effects on American Master's Degrees Obtained in 2 Years

	Dep Var: American Master's Degrees Obtained in 2 Years			
	OLS	IV w/ Shifter Controls		
	(1)	(2)	(3)	(4)
Chinese Masters	0.441^{***}	0.497^{***}	0.284	0.264
	(0.165)	(0.191)	(0.204)	(0.330)
Observations	13828	13828	13828	13828
Mean	420.6	420.6	420.6	420.6
F-stats		53.86	44.38	32.91
Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
Sum of Share			Yes	Yes
Province-Year Indicators				Yes
4 Major-Year Indicators				Yes

Notes: Data on American students are sourced from the NCSES database. These data do not provide information on student enrollment, but only on degrees completed by level of study. In the analysis, we proxy enrollment at each level using degree completions observed a few years later, assuming four years for undergraduate programs, two years for master's programs, and five years for doctoral programs. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). We provide the corresponding first-stage F-stats in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Effects on American Doctorate Degrees Obtained in 5 Years

	Dep Var: American Doctorate Degrees Obtained in 5 Years			
	OLS	IV w/ Shifter Controls		
	(1)	(2)	(3)	(4)
Chinese Masters	0.0158**	0.0434***	0.0437**	0.00378
	(0.00760)	(0.0149)	(0.0179)	(0.0265)
Observations	13828	13828	13828	13828
Mean	34.73	34.73	34.73	34.73
F-stats		53.86	44.38	32.91
Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
Sum of Share			Yes	Yes
Province-Year Indicators				Yes
4 Major-Year Indicators				Yes

Notes: Data on American students are sourced from the NCSES database. These data do not provide information on student enrollment, but only on degrees completed by level of study. In the analysis, we proxy enrollment at each level using degree completions observed a few years later, assuming four years for undergraduate programs, two years for master's programs, and five years for doctoral programs. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). We provide the corresponding first-stage F-stats in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Shifter Level Regressions: Impacts on Other International Students

	(1) Homoskedasticity	(2) Heteroskedasticity	(3) Cluster on Province-Major	(4) Cluster on Province
Panel A: Results on Number of Other International Undergraduate Students				
Chinese Masters	0.266***	0.266***	0.266***	0.266***
	(0.0959)	(0.0994)	(0.101)	(0.0610)
Panel B: Results on Number of Other International Master's Students				
Chinese Masters	0.504***	0.504***	0.504***	0.504***
	(0.144)	(0.160)	(0.142)	(0.109)
Panel C: Results on Number of Other International Doctorate Students				
Chinese Masters	-0.0895***	-0.0895***	-0.0895***	-0.0895***
	(0.0279)	(0.0266)	(0.0225)	(0.0248)
Observations	3572	3572	3572	3572
Number of Cluster			118	30

Notes: Data on Chinese and other international students come from the SEVIS database. The analysis is conducted at the shifter level, with exposure-robust standard errors computed following the method proposed by Borusyak et al. (2022). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Effects on Other International Undergraduate Students

	Dep Var: Other International Undergraduate Students			
	OLS	IV w/ Shifter Controls		
	(1)	(2)	(3)	(4)
Chinese Masters	0.0852***	0.139**	0.197***	0.266**
	(0.0300)	(0.0601)	(0.0745)	(0.127)
Observations	13413	13413	13413	13413
Mean	44.66	44.66	44.66	44.66
F-stats		91.60	67.10	32.66
Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
Sum of Share			Yes	Yes
Province-Year Indicators				Yes
4 Major-Year Indicators				Yes

Notes: Data on Chinese and other international students come from the SEVIS database. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). We provide the corresponding first-stage F-stats in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Effects on Other International Master's Students

	Dep Var: Other International Master's Students			
	OLS	IV w/ Shifter Controls		
	(1)	(2)	(3)	(4)
Chinese Masters	0.180***	0.308***	0.371***	0.504**
	(0.0441)	(0.0796)	(0.0968)	(0.204)
Observations	13413	13413	13413	13413
Mean	49.69	49.69	49.69	49.69
F-stats		91.60	67.10	32.66
Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
Sum of Share			Yes	Yes
Province-Year Indicators				Yes
4 Major-Year Indicators				Yes

Notes: Data on Chinese and other international students come from the SEVIS database. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). We provide the corresponding first-stage F-stats in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Effects on Other International Doctorate Students

	Dep Var: Other International Doctorate Students			
	OLS	IV w/ Shifter Controls		
	(1)	(2)	(3)	(4)
Chinese Masters	-0.0194**	-0.0491***	-0.0520***	-0.0895***
	(0.00796)	(0.0166)	(0.0181)	(0.0322)
Observations	13413	13413	13413	13413
Mean	12.85	12.85	12.85	12.85
F-stats		91.60	67.10	32.66
Year FE	Yes	Yes	Yes	Yes
University FE	Yes	Yes	Yes	Yes
Sum of Share			Yes	Yes
Province-Year Indicators				Yes
4 Major-Year Indicators				Yes

Notes: Data on Chinese and other international students come from the SEVIS database. In the IV specification, we instrument the independent variable using the shift-share variable defined in Equation (5). We provide the corresponding first-stage F-stats in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Shock Balance Tests

Outcome	Coefficient	Std. Error	N
Percent of freshmen from out-of-state	0.0038	(0.0054)	621
Number of Non-resident Alien Undergrads	0.0325	(0.1010)	439
Non-need based aid available (0/1) $\times$100	-0.0120	(0.0156)	712
Offer Master Degree (0/1) $\times$100	-0.0031	(0.0023)	712
Offer Doctorate Degree (0/1) $\times$100	-0.0007	(0.0092)	712

Notes: The outcomes are obtained from the IPEDS and represent changes between 2000 and 2003. Due to missing data for university-level outcomes in the earlier years, the sample is smaller than in the baseline analysis. We regress these outcomes on the change in the shift-share measure from 2003 to 2015, controlling for province and major fixed effects, as well as the sum of shares included in the model. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Shifter Level Regressions: Impacts on Number of Prgrams

	(1) Homoskedasticity	(2) Heteroskedasticity	(3) Cluster on Province-Major	(4) Cluster on Province
Panel A: Results on Bachelor Programs				
Chinese Masters×100	0.289	0.289	0.289	0.289
	(0.329)	(0.279)	(0.242)	(0.186)
Panel B: Results on Master Programs				
Chinese Masters×100	0.985***	0.985***	0.985***	0.985***
	(0.363)	(0.382)	(0.346)	(0.289)
Panel C: Results on Doctorate Programs				
Chinese Masters×100	-0.0146	-0.0146	-0.0146	-0.0146
	(0.230)	(0.214)	(0.201)	(0.192)
Observations	3817	3817	3817	3817
Number of Cluster			119	30

Notes: Data on Chinese and other international students come from the SEVIS database, while data on all the programs are sourced from the NCSES database. We infer the number of programs from the unique major within each university-year using the 4-digit Classification of Instructional Programs (CIP) code. The analysis is conducted at the shifter level, with exposure-robust standard errors computed following the method proposed by Borusyak et al. (2022). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A16: County-level First-Stage Results

Dep Var: Number of Chinese Master's Students in the US			
	(1)	(2)	(3)
Panel A: Restricted to College Towns			
Shift-Share	1.841***	1.901***	1.646***
	(0.200)	(0.324)	(0.229)
Observations	5525	5525	5525
F-stats	84.31	34.45	51.70
Panel B: Restricted to non-College Towns			
Shift-Share	1.275***	0.781	0.748**
	(0.388)	(0.755)	(0.315)
Observations	4355	4355	4355
F-stats	10.79	1.072	5.630
Year FE	Yes	Yes	Yes
University FE	Yes	Yes	Yes
Sum of Share		Yes	Yes
Province-Year Indicators			Yes
4 Major-Year Indicators			Yes

Notes: The data source is the SEVIS database. A college town is a city or town where a university significantly influences the local economy and culture, often with students making up at least 20% of the population. The university may be the largest employer, and many businesses cater primarily to students. We select the American college towns following the definition on Wikipedia. The Shift-Share instrument is created following Equation (5). SE clustered at the university level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$