The Value of US College Education in Global Labor Markets: Experimental Evidence from China*

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Abstract

One million international students study in the United States each year, and the majority of them compete in global labor markets after graduation. I conducted a large-scale field experiment and a companion employer survey to study how employers in China value U.S. college education. I sent more than 27,000 fictitious online applications to business and computer science jobs in China, randomizing the country of college education. I find that U.S.-educated applicants are on average 18% less likely to receive a callback than applicants educated in China, with applicants from very selective U.S. institutions under- performing those from the least selective Chinese institutions. The United States-China call- back gap is smaller at high-wage jobs, consistent with employers fearing U.S.-educated applicants have better outside options and would be harder to hire and retain. The gap is also smaller at foreign-owned firms, consistent with Chinese-owned firms knowing less about American education. Controlling for high school quality, test scores, or U.S. work experiences does not attenuate the gap, suggesting that the gap is not driven by employer perceptions of negative selection. A survey of 507 hiring managers at college career fairs finds consistent and additional supporting evidence for the experimental findings.

JEL classification: I23, I26, J24, J61, J63, M51

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1 Introduction

A million international students study in the US every year, half of whom are undergraduates.[1] Foreign students spend 45 billion dollars on tuition and living expenses—60 percent more than Federal Pell Grant aid in 2017-18—and they contribute to American universities intellectually and culturally. Since visa slots to work in the US are limited, most foreign students are required to leave the country within a few years of graduation. The majority of these students therefore work overseas, yet we know little about the economic returns to an American college education outside the US.

In this paper, I study whether employers in global labor markets value US college education more than domestic options at the interview offer stage. I focus on the case of China as Chinese students account for one-third of international undergraduates in the US and 66 percent of the growth between 2006 and 2016 (see Appendix Figure A.1). They are critical to US institutions that rely on international students for tuition revenue and high SAT scores (Bound et al., 2020; Chen et al., 2020). Though the benefits of a US college education in Chinese labor markets are unclear, the average cost is between \$35,000 and \$45,000 a year (Ma et al., 2017), about 40 times higher than the typical cost in China.

I conduct a large-scale field experiment to assess employer perceptions of college education from US and Chinese institutions. Using administrative data on college enrollment and thousands of actual resumes, I construct a large database of resume characteristics to generate fictitious but realistic job applicant profiles. I submitted more than 27,000 online applications to job vacancies in three major Chinese cities. I sent four applications to each job, randomizing various candidate characteristics, including country and selectivity of the college attended. My experimental design allows me to test, among other things, whether employers are more likely to express an interest in applicants educated in the US but otherwise-identical.

I examine differences in callback rates by different candidate attributes, where a callback is defined as a personalized and positive contact from a potential employer. I focus on comparisons of callback rates between applicants educated in the US and in China. I also examine how callback rates differ by institutional selectivity, both within and across the two countries.

My fictitious job applicants apply for vacancies in business and computer science occupations posted on a large online job board. They are either graduating seniors or

[1]Source: Institute of International Education (2017).

recent college graduates. I select full-time entry-level jobs that require a bachelor's degree and minimal work experience, since as Deming et al. (2016) point out, college credentials are more relevant to employers for these types of positions.

I find two main patterns in callback rates: First, job applicants from the typical US institution in my sample have a lower callback rate than applicants from the typical Chinese institution. On average, applicants with US degrees are 3 percentage points less likely to receive a callback than those with similar degrees from China, which reflects an 18 percent decrease in the probability of receiving a callback. The US-China gap is larger for computer science jobs than business jobs.

Second, within both the US and China, job applicants from very selective institutions have higher callback rates than applicants from the least selective institutions. There is a 9 percent increase in the probability of receiving a callback in the case of US and a 13 percent increase in the case of China. Perhaps more surprisingly, applicants from very selective US institutions (e.g., University of California – San Diego) are 7 percent less likely to receive a callback than those from the least selective Chinese institutions (e.g., Beijing City University).

Leveraging the experimental design and data collected about job vacancies, I test several mechanisms that may explain the lower callback rates for applicants educated in the US I find that my data are most consistent with two hypotheses. First, a large part of the US-China gap in callback rates can be explained by perceived better outside options for US-educated applicants. Employers believe, correctly or not, that applicants from US institutions have better options, making them harder to attract and retain than those educated in China. The perceived cost of filling an opening can therefore prevent employers from contacting qualified candidates. I use posted salaries to proxy for jobs' value relative to potential outside options. The US-China gap is largest among low-wage jobs and smallest among high-wage jobs.

Second, part of the US-China gap can be driven by firms in China knowing less about an American education. Relative to foreign-owned firms, Chinese-owned firms are likely to be less experienced in hiring US-educated workers and have less information about American education. I am able to identify hiring firms as Chinese-owned or foreign-owned, and the gap in callback rates is smaller for foreign-owned firms.

My data run contrary to two alternative hypotheses. First, the US-China difference in callback rates is not likely driven by perceived negative selection of students who study in the US and those who return to China. I randomly signal pre-college credentials on some job applications—either graduating from an elite ("exam") high school or receiving a high score on the Chinese national college entrance exam. Additionally, I randomly signal US work experience. Neither signal decreases the US-China gap. I conclude from these results that employers are not avoiding applicants from US institutions because they associate receiving an American education with negative selection on unobserved quality. This is also consistent with the fact that the gap is smaller at high-wage jobs.

Second, the gap in callback rates is not likely driven by the existence of Chinese institutions' networks with local hiring firms who prefer graduates from these local colleges. The gap persists when access to local employer networks is eliminated by using job applications in a city in which neither the Chinese- nor the US-educated applicants studied—i.e., when a graduate from a university in Beijing or Shanghai applies for a job in Guangzhou.

To probe mechanisms further and cross-validate experimental results in an offline setting, I surveyed 507 employers at college career fairs in China using a vignette choice-experiment method. Hiring managers are asked to choose between two otherwise-identical candidates for an interview—one educated in the US and one educated in China. Once the choice is made, they are asked the reason for making the decision. They are also surveyed on their knowledge of the institutions and prior hiring experience with US-educated candidates. The survey results are consistent with the experiment for both differential callback rates and mechanisms. Additionally, they suggest that concern about workplace cultural fit may also drive employers' favoritism towards Chinese-educated candidates.

The results in this paper have two broad implications. First, taken at face value, my results raise the question of whether the increased cost of studying in the US for Chinese students can be only justified by better job prospects in China. The cost of college for these students is about 40 times higher in the US than the typical cost in China (about $1,000 per year). Furthermore, close to 90 percent of Chinese undergraduates in the labor market leave the US within a few years after graduation, and so will primarily be earning their returns to schooling in the Chinese labor market.[2] Even though the US-China gap in callback rates decreases in posted salary, it is not positive even among the highest paying jobs. Therefore, reasons such as consumption value (e.g., enjoyment of US culture or school prestige) and the small probability of being able to work in or immigrate to the US

[2] About 76 percent of Chinese undergraduates in the US participate in labor markets upon graduation—68 percent leave the US right away and 32 percent get Optional Practical Training (OPT). About one-third of students on OPT obtain work visas. While tracking foreign students is very difficult, Appendix Figure A.2 provides estimates of transition probabilities using the best data I had access to while writing this paper.

may be quite important in driving students' decisions on where to invest in human capital. It is also possible that American education takes longer to pay off, or Chinese students in the US are misinformed about the returns, which is consistent with evidence that students are poorly informed about labor market returns to college education in their own country (e.g., see Wiswall and Zafar, 2014 for a US case and Hastings et al., 2015 for a Chilean case). Note that Chinese students often obtain information on American education from agencies that profit by assisting US college applications. This intermediary industry in China has a conservatively estimated size of $4.6 billion (China Citic Bank and Nielsen, 2015), and it has more incentive to advertise positive aspects of an American education.

Second, financial contributions from international students to US universities is increasingly important given the current crisis faced by US higher education. If US colleges want to maintain or increase their Chinese enrollment, it could be important to assist students in the transition from an American education to a Chinese workplace, perhaps via reducing information frictions for employers in China or helping students better navigate the job search process. The media has suspected that disappointment of returns to US college degrees in Korea led to a decrease in Korean student enrollment in the US in recent years (Fischer, 2014). In China, employment outcomes of returning students from the US has received a great deal of attention. In fact, key results of this paper went viral in China within a few days—countless media outlets reported and discussed the results, including a report by the National Business Daily that attracted 200 million views on China's Twitter-like Weibo.[3] Some institutions have already started to invest in international career services.[4] For example, Ohio State University has an office in Shanghai dedicated to assisting students in finding jobs in China (Fischer, 2017). There is also an expanding industry of job search assistance for returning Chinese students (e.g., DreambigCareer, International Ideal, and UniCareer). The primary services include connecting students to employers in China and providing internship opportunities.

The findings in this paper contribute to our broad understanding of the labor market value of a US college education. A large literature in labor economics and education has studied the value of a US college education in general and institutions of different quality and types on outcomes including earnings (e.g., Card, 1993; Kane and Rouse, 1995; Dale and Krueger, 2002; Dale and Krueger, 2011; Black and Smith, 2004; Hoekstra,

[3]Examples of these links are provided on the author's website.

[4]The author has also been contacted by people who are working with large US universities to improve their Chinese students' job outcomes, as well as entrepreneurs who are building up companies that help international students' job placement.

2009; Zimmerman, 2016; Chetty et al., 2017; Mountjoy, 2018), as well as callback rate differentials (Darolia et al., 2015; Deming et al., 2016). While all previous studies have focused on labor markets in the US, we know little about the labor market value of a US education in foreign countries.

Research on the value of US education abroad is challenging due to data limitations and a lack of exogenous variation in receiving education in the US Detailed educational experience, such as institution and country of college degree, is rarely observed in standard datasets. Decisions about which country to study in and where to work can involve complicated selection on unobservables, which renders identification difficult for observational studies. To the best of my knowledge, this paper is among the first to provide causal evidence on the value of US postsecondary education in foreign labor markets.[5]

This paper also contributes to the immigration literature on international students.[6] In 2017, the number of student visas (F-1) issued was larger than the number of work visas (H-1B) and the number of skill-based green cards combined.[7] Despite the large number of international students in the US, research on this population is limited compared to studies on other types of foreigners. Existing studies focus on how US institutions interact with international students (e.g., Shih, 2017; Bound et al., 2020; Chen, 2021; Chen and Liang, 2022).

The experiment in this paper follows the line of work that uses resume audit studies to assess how employers respond to various characteristics of job seekers (e.g., Bertrand and Mullainathan, 2004; Oreopoulos, 2011; Kroft et al., 2013; Eriksson and Rooth, 2014; Farber et al., 2016; Farber et al., 2017; Agan and Starr, 2018; Farber et al., 2018).[8] Notably, Deming et al. (2016) find that US employers are less likely to reach out applicants with bachelor's degrees from for-profit institutions than those from local public institutions.[9]

[5]A concurrent study (Priebe, 2021) conducts a resume audit study to look at the value of US college education in Indonesia.

[6]Relatedly, my findings add to studies on labor market returns abroad to spending time in the US. Few papers have examined the returns to migration after leaving the US (Reinhold and Thom, 2013; Abramitzky et al., 2017) and they do not rule out the possibility that migrants can enroll in school while working. I provide evidence on the value of time spent in the US in the case of international students, and I distinguish between the value of human capital investment and the value of work experience.

[7]Visa statistics are from the Department of State, travel.state.gov/content/travel/en/legal/visa-law0/visa-statistics, and green card statistics are from the Department of Homeland Security, www.dhs.gov/immigration-statistics, last accessed on August 10, 2018. Some degree-seeking students use visas for exchange students and visiting scholars (J-1), which is twice the number of work visas issued.

[8]See Bertrand and Duflo (2017) and Gaddis (2017) for comprehensive reviews of audit studies.

[9]Darolia et al. (2015) also conduct an audit study to learn about for-profit colleges. Their focus is on associate degrees and certificates instead of bachelor's degrees.

One of the limitations in Deming et al. (2016) is that they do not test directly whether employers associate for-profit college degrees negatively with pre-college determinants of productivity. As noted earlier, I address this directly in my setting by experimentally varying two signals of pre-college credentials.

Overall, my experimental design allows me to test a rich set of mechanisms. This is the first paper of which I am aware that uses a vignette method to complement and cross-validate a resume audit experiment. The consistency between the experiment and the survey adds to recent work (Mas and Pallais, 2017) that find survey-based choice experiments with vignettes can elicit responses similar to real-world settings. My results on callback differentials by employer type also confirms the importance of understanding employer heterogeneity in audit studies (Kline and Walters, 2019).

The rest of the paper proceeds as follows. In Section 2, I provide institutional background on the higher education market for Chinese students in the US and in China. I use this information to guide choices of institutions, and I discuss potential limitations of my field experiment. Section 3 contains a detailed description of the experimental design, including the randomization structure, choice of degree programs and labor markets, resume construction, and a brief description of the employer survey. In Section 4, I present the main results of the experiment, and in Section 5, I investigate the relative importance of the alternative mechanisms described briefly in the introduction that could be driving the core results of lower callback rates for US-educated applicants. Section 6 concludes.

2 Background and prior research

2.1 Higher education markets for Chinese students

The US has historically been the most popular destination country for international students seeking higher education, hosting nearly a quarter of all students studying abroad in 2017.[10] The size of international student body in the 2016-17 academic year is similar to the size of degree-granting for-profit institutions, or four times of the University of California system. Between 2006-07 and 2016-17, international student enrollment in the US increased dramatically, rising 48 percent for graduate students and 84 percent for undergraduates. International undergraduates account for more than half of all international students in the US As shown in Appendix Figure A.1, the increase in undergraduate

[10]Source: Institute of International Education's Project Atlas, https://www.iie.org/Research-and-Insights/Project-Atlas, last accessed on May 3, 2018.

enrollment is primarily driven by students from China, contributing to 66 percent of the total increase over this period. In 2016-17, about 143,000 undergraduate Chinese students enrolled in US institutions, compared to slightly less than 10,000 in 2006-07.

Both the supply side and the demand side of the market have contributed to the increase in Chinese students seeking a US undergraduate education. On the one hand, state governments in the US made significant appropriation cuts for higher education during the Great Recession. This created additional incentives for public universities to recruit overseas students, who pay out-of-state tuition and fees with no institutional aid.[11] Bound et al. (2020) estimate that a 10 percent reduction in state appropriations is associated with a 12 percent increase in foreign student enrollment at public research universities.

On the other hand, large economic growth combined with a regime switch to a flexible exchange rate made US universities more affordable for Chinese families. In particular, urban households experienced especially large gains in wealth as a result of rising house prices (Fang et al., 2016). According to the 2017 China Household Finance Survey, the median household wealth is $389,000 in Beijing and $329,000 in Shanghai, which is perhaps enough to afford the average annual cost of an American college at around $35,000 for public universities and $45,000 for private universities (Ma et al., 2017). Meanwhile, a population boom and secondary school expansion in China have contributed to a drastic increase in the number of high school graduates, which further increased potential demand for higher education abroad.[12]

China has put tremendous effort into promoting college access; over 500 institutions granting bachelor's degrees have opened over the last decade. As of 2016, China has 1,237 institutions granting bachelor's degrees, with an average enrollment of 13,000 undergraduates, in contrast to about 2,564 institutions in the US with an average enrollment of 3,900 (NBSC (2017) and the 2016 IPEDS Fall Enrollment Survey).

Nevertheless, capacity at high-quality Chinese institutions remains limited. The notion of elite institutions is clearly defined and widely accepted in China. In November 1995, China announced *Project 211*, a program to build around 100 high-quality institutions for the 21st century. In May 1998, *Project 985* was announced to further invest so that some of the *Project 211* universities would be "world-class." By 2008, there were 112 institutions

[11] Based on administrative data on F-1 student visa records between 2014 and 2016, only 3 percent of all funding for tuition and living expenses comes from hosting US institutions for Chinese students seeking bachelor's degrees.

[12] According to NBSC (2017), the number of high school graduates in China increased from 3 million in 2000 to its peak of over 8.4 million in 2008 and was still at that level in 2016.

under *Project 211*, and 39 were also under *Project 985*. The development of these programs was part of China's Five-Year Plans. The covered institutions received a significant amount of resources in many respects; for example, 2.2 billion USD were devoted to *Project 211* institutions between 1996 and 2000 (Li, 2004).

Project 985 and *Project 211* institutions have priority in admitting high-quality students. Specifically, China's college admissions process is centralized and determined by a high-stakes entrance exam (Sargent et al., 2011; Chen et al., 2022). Every year provincial governments set exam score thresholds for applying to any college and applying to elite colleges, which mostly consist of *Project 211* institutions (Liu, 2016).[13] The thresholds guide each school sets its own cutoffs to guide college applications, and *Project 985* institutions typically have higher cutoffs than other *Project 211* institutions. Based on public data released by schools, less than 2% of 10.9 million takers of the 2021 entrance exam was admitted to *Project 985* schools and less than 6.6% was admitted to *Project 211* schools.

Because seats at high-quality institutions are scarce in China relative to the size of its population, many Chinese students are attracted to reputable institutions in the US Based on administrative data on F-1 visa records for the entering class in the fall of 2014, about 80 percent of all Chinese undergraduates in the US enrolled at one of the 300 schools listed on the 2017 US News ranking of national universities. Note that while comparing institutions across countries is difficult, more US institutions make it into various world rankings of universities than do Chinese institutions. Appendix Figure A.3 shows that among ranked schools, US institutions are also much more highly ranked. In addition, since public universities have monetary incentives to enroll Chinese students, it is not surprising that nearly 70 percent of Chinese students are enrolled at public institutions. These observations drive my choice of schools to be included in the experiment, which is described in Section 3.3.

Undergraduate education at US and Chinese institutions is similar in many ways, with some notable differences. As in the US, Chinese institutions offer a four-year curriculum for a typical bachelor's degree. Students spend the first one to two years taking general courses and the remaining years taking major courses. However, students in China generally have less freedom in choosing what classes to take compared to students in the US, and for most students in China, their majors are determined at the time of admission. Furthermore, the college graduation rate at Chinese universities is estimated to be above 97

[13]Starting in 2017, a few places no longer set these thresholds so that all students could be considered by all schools at the same time.

percent.[14] By comparison, while graduation data are not separately available for Chinese students in the US, the 6-year graduation rate for all international students is 70 percent, based on the 2016 IPEDS. This rate is likely to be higher for students from China, as SAT score is positively correlated with college completion (Shaw, 2015) and Chinese students have higher SAT scores than the average foreign student (Chen et al., 2020).

Attending US institutions imposes some employment limitations for Chinese students. The US immigration system offers two practical training programs that allow international students to work in the US. Curriculum Practical Training (CPT) permits students to work in summers or during school time, and Optional Practical Training (OPT) is used after graduation. The OPT lasts one year for non-STEM majors and two to three years for STEM majors, depending on the year of approval. Upon graduation, students who find a job in the US often start with OPT while simultaneously participating in the work visa lottery.

Lastly, it is important to note that Chinese students studying in the US may have different experiences in high school. Since the college admission process is different in the two countries, students who decide to apply for colleges in the US need to spend time studying for tests such as TOEFL, SAT, and AP, participating in additional extracurricular activities, and writing college application essays. In contrast, students who decide to apply for colleges in China spend most of their time studying for the national college entrance exam.

2.2 Assessing employer preferences with audit study

Despite the popularity of American higher education across the globe, its value in labor markets abroad is not very well understood. Research on this problem is challenging due to data limitations on observing workers' detailed education experience and sorting into an education system on unobservables. Using a resume audit study design, I randomly assign institutions and degrees to otherwise-identical resumes (in expectation), and I estimate the causal impact of having a US college education relative to a Chinese college education on receiving callbacks from employers in China.

There are several potential limitations when interpreting results from resume audit studies. First, the detected differences in callbacks reflect only employers' beliefs about applicant characteristics, such as quality inferred from different types of institutions, and

[14] Marioulas (2017) catalogs graduation rates for a diverse mix of 187 four-year institutions in China and finds the average graduation rate is 97.3 percent. The Ministry of Education in China also announced that the annual college dropout rate is only about 0.75 percent (Wu, 2011).

not the true value-added of the institutions. Employer beliefs are influenced by the information employers have on the institutions. I examine several potential mechanisms of how different beliefs lead to differences in callback rates by US and Chinese institutions, leveraging both the experimental design and additional data collected about the vacancies from the job postings. My employer survey provides both a cross-validation of the tested mechanisms and evidence on explanations that cannot be tested directly.

Second, jobs posted online may be selected so that they do not represent the types of jobs faced by the applicants of interest, or employers may have a different perception about job applicants looking for jobs online. However, it has become increasingly common for both employers and college graduates to use online platforms. The internet job boards industry has expanded dramatically in China over the last five years. In 2016, about 144.5 million job seekers were looking for jobs online, and about 4.3 million employers posted at least one job (iResearch, 2017). Online job boards are important for both college students in China and returning overseas students. A recent report by Zhaopin (2016) shows that 60 percent of college students in China have used online job boards as their channel to look for jobs. This is the most widely used method, followed by career fairs (30 percent). Job applicants with US degrees have less access to local career fairs and are even more likely to rely on online platforms while searching for jobs. A survey of returning overseas students in China conducted by the Center for China and Globalization and Zhaopin.com (hereafter, CCG and Zhaopin, 2017) finds that about 63 percent of returning students from abroad have found a job using online platforms. Besides, a different survey conducted by UniCareer (2019), a career development firm, finds that online job boards is the most popular method used among returning Chinese students when looking for jobs. Hence, it is unlikely that employers in China perceive job applicants who use online boards differently.

The survey results mentioned above imply that family networks play a limited role in the job search for returning Chinese students. Given that Chinese students in the US are from various places in China, it is also hard for local family networks playing a critical role in popular destination cities for returning students. The rise of job search assistance companies for returning students such as DreamBigCareer and UniCareer further indicates the demand for network connections and search assistance outside of family networks.

In Appendix Table A.1, I show that the jobs applied for in my experiment (hereafter, target jobs) share similar characteristics with jobs in China held by workers educated abroad based on 3 external surveys. The job characteristics include wage, firm ownership, firm size, and occupation. This evidence establishes that the target jobs are relevant to returning Chinese students and are representative of their actual employment.

Third, as in other audit studies, my main outcome is receiving an employer callback. Differential callback rates by institutions do necessarily lead to differences in job offers or wages. I partially address this concern by distinguishing interview offers from regular callbacks and use this as an alternative measure of outcome—the applicant is one step closer to a job offer—and find no difference in my main results. Two papers further increase the likelihood that callback rates may be linked to other job outcomes. First, in an in-person audit study, Mincy (1993) finds that group differences in callbacks and job offers are similar. Second, using a regression discontinuity design, Jia and Li (2017) estimate an earnings return between 30 and 40 percent for attending very selective and selective Chinese institutions relative to inclusive institutions. This is broadly consistent with my result that applicants from very selective and selective Chinese institutions are 13 percent more likely to receive a callback.

While I cannot observe employer hiring decisions with an audit study, I ask hiring managers in the employer survey whether US-educated candidates perform better than candidates educated in China during entry-level job interviews. It turns out that 33 percent of hiring managers said similar performance, 40 percent said Chinese-educated candidates perform better, 18 percent said they do not know, and only 9 percent said US-educated perform better. Hence, there is no clear evidence that US-China gap in job offers would be significant reversed after the stage of receiving job interviews.

Despite these potential limitations, an audit study allows me to both randomly vary and perfectly observe all information about job candidates observed by employers at the interview stage. I strive to make the fictitious resumes appear similar to resumes of real applicants and to create resumes with characteristics drawn from the "common support" across all types of institutions. My experiment reproduces an important part of the actual job search process, and it is informative about employers' preferences for marginal students who could plausibly have attended either a US or a Chinese institution.

3 Experimental design

3.1 Study setting: Degrees, occupations, and labor markets

I focus on bachelor's degree programs in business and computer science. These two majors account for half of all Chinese undergraduates in the US who entered in the fall of 2014.[15] Table 1 lists occupations and degrees studied in the experiment. For business-related degrees, I apply for jobs in two broad business occupations: accounting/finance/banking and sales/customer service/marketing. For degrees in computer science, I apply for jobs in software/network/IT occupations. Business and computer science jobs require distinct sets of skills. Column 3 of Table 1 provides some sample job titles. The occupation choices are consistent with the classifications of degree programs published by the National Center for Education Statistics.[16] Most job-seeking activities take place in these occupations for applicants from corresponding degree programs, and CCG and Zhaopin (2017) find about half of returning Chinese students from abroad work in these jobs.[17]

The source of target jobs is a large, nationally recognized online job board. During December 2018, this website listed 3.4 million unique vacancies over successive three-day periods; about 20 percent of the jobs require a bachelor's degree. Column 4 of Table 1 shows that business and computer science job vacancies account for half of all full-time jobs that require a bachelor's degree.[18]

I submit applications for full-time positions that require a bachelor's degree and two or fewer years of work experience, and I do not consider positions with a posted salary below the 5$^{\text{th}}$ percentile to exclude low-quality jobs. Every time an application is submitted, a new resume is filled out using the standard template provided in the job board's system.[19]

[15]Based on administrative records of individuals with F-1 student visas, which classify programs using the Classification of Instructional Programs (CIP) codes. See Appendix Table A.2 for enrollment shares by program. While data on degrees awarded to Chinese students are not available, Chinese enrollment shares by program are very similar to the shares of degrees awarded to all foreign students reported by IPEDS.

[16]IPEDS classifies degree programs by occupation using CIP codes. Deming et al. (2016) also use this method to select occupations.

[17]For each broadly defined field of study, a large national online job board publishes a list of occupations with shares of students searching for jobs in that field.

[18]Following Deming et al. (2016), I divide the number of full-time job vacancies requiring a bachelor's degree in the last 24 hours for a given occupation by the total number of full-time job vacancies requiring a bachelor's degree in the same period. I calculate this share for three consecutive days in December 2017 and take the average to get the shares in Table 1. The shares are robust when using data from September 2017 and April 2018.

[19]In contrast to a typical US audit study, which applies for jobs by emailing or uploading pre-generated resumes, more effort is required to fill out new job applications every time. One exception that fills out job applications in the US is Agan and Starr (2018).

Each vacancy posting contains information about the firm, job requirements, and expected salary. This information is collected using a web scraping program. The procedure for submitting job applications is described in Appendix C.

The main experimental sample consists of jobs in the two largest cities in China, Beijing and Shanghai. Labor markets in these cities provide many employment opportunities for college graduates, and account for 30 percent of all full-time job vacancies that require a college degree in China, based on vacancy counts collected from a three-day period in December 2017. A recent survey by CCG and Zhaopin (2017) shows that they are the most popular destinations for students returning from abroad, and receive about 40 percent of returning students. In addition, Beijing and Shanghai have more bachelor-degree-granting institutions than any other cities in China, and the variety in institutional quality ensures that colleges of different quality can be studied. I also submit applications for a supplementary sample of business jobs in Guangzhou to consider the role of local employer networks. Details are discussed in Section 5.4.

3.2 Randomization structure

For each target job, I send four fictitious but realistic job applications (hereafter, resumes). I randomly vary resume characteristics, including country and selectivity of the undergraduate institution. Figure 1 summarizes the key randomization structure. Following the general practice in the audit study literature, two of the four resumes are assigned degrees from colleges in China and the other two are assigned degrees from colleges in the US. Within the two resumes assigned to the same country for college education, the selectivity of each institution is randomly drawn without replacement from three groups: very selective, selective, and inclusive. Note that comparing institutions across countries on the same measure is difficult, and relevant data are often not available for all institutions. For this reason, I define selectivity groups separately for institutions within each country.

Selectivity groups in China: As discussed in Section 2.2, there is a widely accepted notion of selective institutions in China, based on whether an institution is listed under two government programs, *Project 985* and *Project 211*. I define institutions under *Project 985* as *very selective*, institutions under *Project 211* but not under *Project 985* as *selective*, and the remaining four-year colleges offering a bachelor's degree as *inclusive*.

Selectivity groups in the US: I use the 2017 US News ranking of national universities to guide my definition of selectivity groups for US institutions. I define an institution as *very* *selective* if it is ranked among the top 50 by US News, *selective* if ranked between 51 and 100, and *inclusive* if ranked between 101 and 250. The US News ranking is commonly used by Chinese students during the application process. For example, the five most popular Chinese agencies that assist students with American college applications list the US News rankings on their websites.[20]

The experimental results would be misleading if institutions were systematically classified into the wrong selectivity group. This is unlikely a concern for two reasons. First, in Section 3.3, I provide additional evidence that the definitions of college selectivity groups in both the US and China are reasonable. The results show that within each country, my definition of a more selective group of institutions is more likely to be highly ranked by the US News' world ranking of universities and have higher test score percentiles for enrolled students. In addition, US and Chinese institutions are comparable in terms of test score percentiles within each selectivity group, although US institutions are higher ranked on average in all selectivity groups. Second, the experimental results show that callback rates increase in the defined institutional selectivity group within each country, and that applicants from very selective US institutions are no more likely to receive a callback than applicants from the least selective Chinese institutions. Hence, regrouping institutions by selectivity will not change the result that applicants from sample US institutions systematically have lower callback rates than those from Chinese institutions.

Other resume characteristics: In addition to randomizing college location and selectivity within jobs, I randomly vary several other resume characteristics across jobs in order to test potential mechanisms by which employers may treat degrees differently. These include a signal of being a graduate of a local elite high school, work status (graduating senior or have graduated and working full time), and having work experience in the US (for applicants with a US education only). Because these characteristics may also predict employers' callback, I randomize them *across* jobs instead of *within* jobs to maximize the power of the main effect of institutional characteristics (Deming et al., 2016). Since prior work has shown that gender influences callback, I also randomly assign gender across jobs. While audit studies in the US signal gender via names, gender is a required field in the standard application template provided by the online job board in my study.

Job applications were sent out during the two hiring seasons for graduating seniors and recent college graduates in China: October to December 2017 and March to May

[20]Last checked on June 19, 2018. China Citic Bank and Nielsen (2015) survey students studying abroad to rank agencies by popularity.

2018. Because results from the fall job season indicated that the callback rate is different by the country of college degree, I randomized an additional resume characteristic in the spring season to explore one of the potential mechanisms. Specifically, I randomly signal a high score on China's college entrance exam among job applicants with US degrees. This characteristic is randomized within jobs in order to maximize power when identifying the test score coefficient. Note that because the type of college in China attended by applicants from Chinese institutions already signals their scores on the entrance exam, I do not include a test score on their resumes.

I follow the standard practice in the literature, in which four resumes for each job are sent out over two to three days with at least a 4-hour gap in between to reduce the likelihood that employers suspect they are linked. The sending order is randomized. Employers' response to each application is carefully tracked via phone, text messages, and emails. A *callback* is defined as a personalized positive contact from employers. This rules out denials of job applications and general messages sent to all applicants. When recording callbacks, I distinguish whether an employer offers an interview from a request for more information. See Appendix C for additional details of the experiment's implementation.

3.3 Resume construction

Institutions: US institutions in this study are chosen to represent the majority of Chinese students. Using administrative data on foreign students with F-1 student visas, I sample US institutions from the universe of schools attended by Chinese students seeking a bachelor's degree. I finalize the set of sample institutions with two selection criteria. First, I focus on schools ranked by the 2017 US News ranking of national universities. I exclude liberal arts colleges and schools not ranked or ranked below 250.[21] As noted in Section 2.1, Chinese students in the US are largely concentrated in high-quality institutions. Second, I impose a minimum enrollment size: A selected school must enroll at least 30 Chinese students from the 2014 cohort, and more than 15 of them must be in either business or computer science programs. This size requirement increases potential familiarity with American institutions in Chinese labor markets.

The experimental sample contains 111 institutions in the US, and they enroll 72 percent of all Chinese students who started in the fall of 2014 seeking a bachelor's degree. Of the

[21]This left 78 percent coverage of all Chinese students who started in the fall of 2014. Note that the US. News assigned ranks to 300 national universities for 2017. Liberal arts colleges and schools ranked between 251 and 300 account for only 7 percent of Chinese enrollment.

total, 71 are public institutions, which account for 78 percent of Chinese enrollment at sample schools. This is consistent with the fact that in general, Chinese students are concentrated in public schools. Institutions such as Harvard and Princeton are not in the sample, because they do not meet the minimum enrollment size. Instead, examples of typical sample institutions are the University of California-San Diego, Michigan State University, and Arizona State University; these are classified as very selective, selective, and inclusive, respectively. Appendix Table A.3 lists all of the sample US institutions and their selectivity group.

Chinese institutions are chosen from the official list of all postsecondary institutions published by China's Ministry of Education. I exclude specialized and strategic schools, and I use local institutions that grant bachelor's degrees in Beijing and Shanghai in order to avoid employers' concern about potential selection based on who leaves their hometown for college and who returns. Both cities attract most of their high school graduates to stay for college by allocating more seats to these students, and nearly all local students stay to work upon graduation (Beijing Department of Education, 2016). This leaves 36 institutions in Beijing and 26 institutions in Shanghai. Tongji University, Central University of Finance and Economics, and Shanghai Lixin University of Accounting and Finance are examples of typical Chinese institutions within the very selective, selective, and inclusive groups, respectively. Appendix Table A.4 lists all of the Chinese institutions used in this study and their selectivity group.

Figures 2 and 3 compare sample institutions across countries using the 2018 US News Best Global Universities ranking and percentile of the average test score for enrolled students, respectively. Three important patterns can be observed. First, my definitions of selectivity groups do a good job of distinguishing institutions within each country; both the average ranking and the average test score percentile increase with college selectivity. Second, sample schools are quite comparable in terms of test score percentiles across countries, both overall and within each selectivity group, except that test score percentiles are lower for inclusive Chinese institutions than inclusive US institutions. Lastly, while sample US institutions are more highly ranked than Chinese institutions on average, the distribution of world rankings are similar to that of all ranked schools (see Appendix Figure A.3).

Institutions that enroll more Chinese students in relevant programs are more likely to be included in this experiment. Degree programs are sampled to be representative of the actual Chinese enrollment within each selectivity group and labor market. I use Chinese enrollment of the 2014 entering class as sampling weights (probabilities), and institutions selected are roughly proportional to their share of enrollment in sample programs.[22] Enrollment data for US institutions are based on administrative records of student visa recipients, obtained from a Freedom of Information Act (FOIA) request to US Immigration and Customs Enforcement. I collect enrollment data for Chinese institutions from publications on China Education Online, which aggregates admissions information from individual institutions in China.[23] Examples of typical institutions provided previously have large sampling weights.

Work experience: My goal is to create work experience that is realistic and representative of job seekers from each type of institution. To do so, I obtained actual resumes from a large online job board. I sample thousands of job seekers from the same degree programs looking for positions in the same occupations and cities as in my experiment. These job seekers are from similar age groups, but were on the labor market in the previous academic year.[24] I populate a number of work history templates from this large database of realistic resumes and assign them randomly to degrees from different institutions.

Another goal when generating work experience is to have experience of similar quality across templates, so that differences in educational institutions are more salient to employers when deciding whom to invite for an interview. Following the spirit of Deming et al. (2016), I select work histories from the "common support" of resumes with different types of institutions for a particular labor market, so that the experimental estimates isolate the marginal impact of educational institutions for students with these work histories.

For students with business degrees, a work history profile contains two summer internships prior to graduation and a full-time job if the student has graduated. There is one less summer internship for students with degrees in computer science. These are the most commonly observed patterns from the real resume bank, both within and across

[22]While Deming et al. (2016) use actual degrees awarded as weights in their study of for-profit institutions in the US, such data are not available for Chinese students. My enrollment data provide a very good approximation for two reasons. First, college graduation rates in China are estimated to be above 97 percent, and the graduation rate for international students at sample institutions is 78 percent, based on 2016 IPEDS. Second, the data on student visa records reflect their most recent enrollment status as of the request approved date, June, 2017. A school is required to update a student's record in cases such as changing programs, revising completion dates, and traveling internationally.

[23]Data on actual enrollment by degree programs in China are not publicly available. I use planned enrollment as a proxy, which is announced by schools after China's college entrance exams take place. These numbers are very close to the actual enrollment, as college-student matching is centralized and schools are experienced in this process.

[24]This is to avoid potential overlaps between real job seekers and the fictitious job seekers, since job seekers may use multiple job boards at the same time.

each type of institution. Appendix C provides additional details on resume construction.

3.4 Companion employer survey

The field experiment can identify causal relationships, but is constrained in what and how mechanisms can be revealed. My companion employer survey is designed to supplement the experiment by providing additional evidence on potential mechanisms in a different setting and addressing questions that cannot be answered by the experiment.

To find hiring managers with experience in the interview process for positions similar to the target jobs, I worked with a survey company to collect data from employers at 50 local career fairs in Beijing between October 2018 and May 2019. The career fairs were for current college seniors and recent college graduates, and they were either hosted on university campuses or at the career development unit under the Beijing Department of Education. The survey team arrived prior to the career fairs and distributed the survey (via a QR code) to hiring managers. Respondents are screened by a few questions to ensure that they have relevant hiring experience. A total of 507 unique hiring managers completed the survey. Successful respondents received a small gift and participated in a lottery draw for a prize of 1,000 RMB (or $155). 55% of the surveyed employers use the same online job board in the experiment and 90% of them use some online recruiting methods. Characteristics of the employers are summarized in Appendix Table A.1.

The employer survey consists of three parts. Hiring managers are first asked about their demographic backgrounds, firm characteristics, and the job opening that they have the most hiring experience with. The second part is the core, where respondents are prompted with a vignette that sets up a hypothetical scenario in the hiring process:

> *Imagine your firm is hiring for an entry-level job in XXX occupation that requires a bachelor's degree. There are two candidates with undergraduate education in relevant major, having resumes that are similar in every respect (e.g. major, gender, Hukou, description of work experience, software skills etc.), except they are attending or have graduated from different schools.*

The survey lists two universities (one US and one Chinese) and asks the hiring manager to choose only one candidate to offer an interview. Multiple choice is not allowed in order to create more variation in an anticipated small sample size. Schools are randomly selected using the same sampling weights as in the field experiment. School selectivity is randomly drawn from the three groups defined previously within each country.

After respondents make a decision on whom to offer an interview, the survey asks for the most important reason that drives their decision. It lists 9 reasons and allows for customized entry. It also asks hiring managers to rate their knowledge about the undergraduate education quality for the two schools listed on a 5-point Likert scale. The core part of the survey appears three times with different schools for each respondent. The survey ends with a few questions to gauge hiring mangers' general attitudes and experience towards American educated candidates. The complete survey in English along with its randomization design and logic flow are in Appendix D.

4 Main results

Table 2 summarizes mean callback rates and number of job applications for the main experimental sample. Out of 26,036 applications submitted for job vacancies, 15 percent received a callback. Most (92 percent) of the callbacks were invitations to interview, and the rest were to gather additional information about the applicant.

Several patterns can be learned from Table 2. First, there exists significant variation in callback rates across cities, occupations, job seasons, gender, and work status. The lower callback rate in Beijing reflects a smaller labor market (measured by population) but a larger supply of college graduates compared to Shanghai (NBSC, 2017). The callback rate for computer science jobs is much lower than for business jobs, in line with the fact the median number of applications received by target computer science jobs is about three times larger than business jobs. Differences in callback rates by job season indicate that the timing of the audit experiment can potentially matter. Consistent with Deming et al. (2016), female applicants have a higher callback rate than male applicants, and, in my setting, these are predominately driven by business jobs. The callback rate for current college seniors is higher than for applicants who are working full time, presumably because employers believe full-time working applicants are harder to attract and do not exert effort to pursue them.

Second, callback rates are quite similar for applicants who signaled graduation from a local elite high school and those who did not list high school. This is not surprising, given that in China, selection into college is a stronger signal of student ability than selection into high school. Similar to the fact that college admission depends entirely on the college entrance exam, high school admission in China is based on students' performance on the high school entrance exam, which is less competitive. The elite schools chosen in this study are top exam schools. Hoekstra et al. (2018) find that attending this type of high school in China increases students' test scores on the college entrance exam and the probability of attending a four-year college.[25] Since nearly all graduates from the chosen elite high schools enroll in four-year institutions, graduation from an elite high school mostly signals an applicant's ability to attend a four-year college in China, with perhaps a higher chance of attending a more selective one. Given that all job applicants list college education on their resumes, the signaling value of an elite high school for the ability to attend a college is largely reduced.

Third, the callback rate decreases in quartiles of posted salary, consistent with the idea that it is harder to obtain jobs with higher pay. Lastly, the callback rate for foreign-owned firms is similar to that for Chinese-owned firms. This is consistent with the fact that in this experiment, jobs posted by foreign-owned firms offer wage similar to those offered by Chinese-owned firms. A signal of elite high school, posted salary, and firm ownership offer opportunities to explore the underlying mechanisms by which employers treat degrees from the US and China differently. These are discussed in Section 5.

Throughout the paper, I estimate the differential callback rate between the US and China using variations of the following linear probability model:

$$\text{Callback}_{ij} = \beta \text{US degree}_{ij} + \text{Other resume characteristics}_{ij}\theta + \omega_j + \epsilon_{ij} \tag{1}$$

where the dependent variable is an indicator for applicant i receiving a callback for job vacancy j, and the independent variable of interest, "US degree," is an indicator for whether a US institution is listed on the job application. Coefficient β is the marginal effect of having a US college education (relative to a college education in China) on the probability of receiving a callback. ω_j represents vacancy fixed effects that are present in the preferred specification. Standard errors are clustered at the vacancy level at all times.

Table 3 shows the main result on the US-China gap in callback rates estimated using equation (1). Column 1 has no additional covariates; column 2 adds controls for work status, job season, gender, labor market, and self-statement template; column 3 further includes name and vacancy fixed effects, which absorb controls that are randomized across jobs: work status, job season, gender, and labor market. Columns 4 and 5 follow the specification in column 3, but show results separately for business and computer science jobs. I report p-values of F-tests for the hypothesis that coefficients from control categories with more than one group are zero.

[25]Relatedly, studies in the US find that attending exam schools has little impact on college quality and college graduation rates (e.g., Abdulkadiroğlu et al., 2014; Dobbie and Fryer, 2014).

Column 1 of Table 3 shows that the raw US-China difference in callback rate is 3 percentage points, and it is statistically significant at 1 percent. This estimate is consistent across different specifications in columns 2-3 and across different occupations in columns 4-5. Relative to the baseline average callback rate of 16.5 percent for job applicants with degrees from China, applicants with US degrees are 18 percent less likely to receive a callback. Breaking the data down by occupation, applicants with US degrees are 17 percent less likely to receive a callback for business jobs and 29 percent less likely for computer science jobs. Appendix Table A.5 reports the main results using interview offer as the outcome. Estimates are quite similar, both quantitatively and qualitatively.

Note that column 2 provides statistical tests for the callback rate difference by group observed in Table 2. Including covariates in addition to the US degree indicator also performs a randomization check. The coefficients on US degrees are the same in columns 1-3, meaning that the key experiment treatment is orthogonal to other resume components and job characteristics. The *p*-values for the F-statistic on names in columns 3-5 are well above 0.1, implying that the generic names chosen for the experiment do not have any effect on callbacks.[26]

Figure 4 summarizes in a bar chart the main result on the differential callback rates by college selectivity group, both across and within countries. It presents mean callback rates in the raw data and their 95 percent confidence intervals. Using the same specification as column 3 of Table 3, but replacing the US degree indicator with five country-selectivity indicators, Appendix Table A.6 reports regression estimates of differences in callback rates for each pair of possible comparison between selectivity groups. Appendix Table A.7 and A.8 report regression estimates for business and computer science jobs, respectively.

Three important patterns can be seen. First, within every selectivity group, US institutions have lower callback rates than institutions in China. Depending on the selectivity group, the difference is between 2.2 and 3.8 percentage points, or 15 to 18 percent relative to Chinese institutions. Second, perhaps surprisingly, the most selective group of US institutions performs worse than the least selective group of institutions in China. The callback rate for job applicants from very selective US institutions is 1.1 percentage points, or 7 percent, lower than that for applicants from inclusive Chinese institutions (*p*-value=0.047). Third, within the same country, applicants from very selective institutions do better than applicants from inclusive institutions, although the difference is smaller for US institutions. The increase in callback rate from inclusive institutions to very selective institutions

[26]Name fixed effects are not included in column 2, because they are correlated with gender.

is about 1 percentage point, or 9 percent, for the US and 2 percentage points, or 13 percent, for China. All three patterns hold qualitatively for business and computer science jobs separately, with very selective US institutions being the most similar to inclusive Chinese institutions for computer science jobs.[27]

The patterns observed in Figure 4 are confirmed using an alternative measure of college selectivity in Figure 5. I group institutions into test score percentile bins for enrolled students within each country and plot the bins against the average callback rates. I plot predicted regression lines using the sample size of each bin as weights. The fitted lines in Figure 5 show patterns similar to those observed in Figure 4.

5 Mechanisms

My main finding on the US-China gap in callback rates suggests that the characteristics of a college education influence employers' decisions on contacting job applicants. The US-China gap reflects employers' perceptions about applicant quality and other characteristics inferred from institutions. Though resumes are carefully constructed so that they are similar in important dimensions, there is a limited amount of information a resume can convey. Therefore, employers may associate an American education with unobserved applicant characteristics that are not relevant to the institutional quality or value-added.

This section discusses four mechanisms that may explain the patterns revealed in the previous section. For each potential theory, I provide empirical tests to leverage the experimental design and data collected on job postings. While I do not claim to cover all possible mechanisms, these empirical exercises address several important channels using the best that can be offered with the experiment. The section ends with additional supporting evidence provided by the companion employer survey.

5.1 Perceived better outside options

Filling a job opening is costly for employers. The hiring cost includes factors such as the time and effort spent to interview and negotiate with candidates and the cost of training. In addition, employers consider how long a worker can be retained. If applicants with better outside options are less likely to accept an offer or stay on a job, the hiring cost can prevent employers from contacting qualified candidates.

[27] One interesting note is that while very selective and selective institutions in China perform similarly for business jobs, very selective institutions outperform selective institutions for computer science jobs.

Employers in China may believe that applicants from US colleges have better outside options relative to applicants from Chinese colleges for two reasons. First, since US institutions are more highly ranked globally than Chinese institutions, employers may assume that US-educated applicants have better options because they are overqualified. This concern is referred to as "reverse discrimination" in the audit study literature (e.g., Bertrand and Mullainathan, 2004; Deming et al., 2016). Second, employers may assume that applicants with an American education are harder to attract and retain because they have better access to US labor markets and immigration opportunities, especially while they are still either studying or working in the US. Therefore, the US-China gap in callback rates may be explained by perceived better outside options

I test for this hypothesis by examining whether the US-China gap is smaller for more attractive jobs. Specifically, I assume that high-quality jobs are more attractive and applicants are more likely to accept an offer and stay in these positions. I proxy job quality by posted salary. The online job board used in the experiment requires that firms post a salary range for every advertised position, and this information is collected for every target job.[28] Table 4 presents the results. Column 1 includes an interaction term between salary and the US degree indicator, and columns 2 to 5 show the US-China gap by quartiles of posted salary (median salary 84,000 RMB, or about $13,000). All columns follow the main specification on controls in column 3 of Table 3.

It is evident from Table 4 that the US-China gap decreases as the posted salary increases. For every $1,000 increase in posted pay, the US-China gap closes by 0.2 percentage point. The gap is the largest at jobs with salaries below the 25^{th} percentile and the smallest at jobs with salaries above the 75^{th} percentile. The difference in the callback gap between these two quartiles is 4.8 percentage points and is statistically significant at 1 percent. The US-China gap persists among jobs paying above the 75^{th}, though its size is much smaller and only statistically significant at 10 percent. Appendix Figure A.4 further plots the estimated gaps by salary deciles. While the same pattern can be observed, the callback gap is not positive, even among jobs with salaries above the 90^{th} percentile.

Results from Table 4 are consistent with the hypothesis of perceived better outside options for applicants with an American education. Concerns about both overqualification

[28]I use the midpoint of the posted salary. Appendix Table A.9 shows that the results are qualitatively the same when using the minimum instead. Deming et al. (2016) use the same test to detect reverse discrimination against applicants with for-profit college degrees in the US. They impute salary data using occupations, because such data are not posted. In addition, for the first time in the literature, I collected the number of job applicants for each posting through a paid service of the job board. I use it as an alternative measure of job quality and results are presented in Appendix Table A.10.

and access to US opportunities can lead to this perception among employers, and distinguishing between the two is difficult. However, given that applicants who are currently in the US have the most access to American resources, access to US labor markets and immigration opportunities is not likely the full story for three reasons.

First, as mentioned earlier, it is very common for Chinese students who studied abroad to return; 84 percent of all Chinese students who completed their studies abroad had returned by 2017.[29] Second, my research design tries to maximize applicants' probability of returning to China. All applicants indicate on their resumes that the city where the job is located is their "home city" and "expected workplace." Both fields are required on the standard application template. In addition, applicants indicate that they have local *hukou*, which is a household registration system that can impose barriers to migration in China (Song, 2014). Third, Table 5 shows the US-China gap in callback rates by employment status of US applicants: (1) returned to work in China; (2) stayed to work in the US; and (3) college seniors who are returning to work in China. The US-China gap persists for those who have returned to work in China. Although the gap is smaller for applicants who have returned than applicants who are returning, it is only statistically significant at 10 percent.

Given that an American education is more expensive, a related concern is that US institutions may signal family wealth. If wealth influences callbacks, perceived better outside options is consistent with the belief that applicants from wealthier families may be more likely to have employment opportunities through family networks. That the gap is smaller at high-wage jobs does not support the idea that employers perceive family wealth as a signal of negative productivity. Nonetheless, as noted in Section 2.1, the median family wealth in Beijing and Shanghai are above the average cost of a college education in the US. Since all applicants in my experiment indicate that they are from Beijing or Shanghai, being able to afford a US education may not signal too much wealth. Lastly, 80 percent of hiring managers from the employer survey indicate that they do not make interview decisions based on candidates' family wealth, while 12 percent indicate they value candidates from wealthier family more and 8 percent value candidates from wealthier family less.

Since the US-China gap in callback rates is largely driven by jobs with salaries below the 75$^{\text{th}}$ percentile, it is important to point out that the majority of US-educated candidates

[29]Source: http://www.moe.edu.cn/jyb_xwfb/gzdt_gzdt/s5987/201803/t20180329_331771.html, last accessed on June 15, 2018. Reported by China's Ministry of Education and based on information reported by Chinese consulates across the world and the Bureau of Exit and Entry Administration.

do not search and get employed at the highest-paying jobs. Based on a recent survey (CCG and Zhaopin, 2017), posted salaries of target jobs are similar to the salaries of jobs held by actual workers in China who were educated abroad (see Appendix A.1).

5.2 Lack of information on US colleges

It is possible that employers in China are not familiar with US institutions. My experimental design selects US institutions with more than a minimum number of Chinese students and samples US institutions based on their Chinese enrollment shares. Nonetheless, Chinese enrollment in the US is only a small share of college enrollment in China.[30] On average, employers are likely inexperienced in hiring US-educated workers and know little about American education. This lack of information can make it difficult for employers to infer applicant characteristics that are important for making callback decisions.

I test this hypothesis by examining whether the US-China gap in callback rates is smaller at firms that are likely to have more information on US institutions. Online job postings contain information on firm ownership, which I collect for every target job. Columns 1 and 2 of Table 6 present estimated US-China gaps for two subsamples: Chinese-owned firms and firms with foreign ownership. Foreign-owned firms are owned or jointly owned by regions outside of China.

The results from Table 6 show that the US-China gap is reduced by about half at foreign-owned firms, consistent with a lack of information on the part of Chinese-owned firms about US institutions. An alternative theory for the gap reduction is that (relative to Chinese-owned firms) foreign-owned firms believe US-educated workers have more firm-specific human capital or fit the company's culture better. Two observations suggest that it is not driving the firm ownership result.

First, English is plausibly a highly demanded skill at foreign-owned firms yet it cannot explain the gap reduction across ownership types. For every target job, I collect information on English requirements. Firms either explicitly list their language requirements as an optional field of the posting, or they state it in the job description. My definition of an English requirement captures both. The data confirms that more jobs at foreign-owned firms require English than jobs at Chinese-owned firms (66 percent versus 22 percent). Columns 3 to 6 of Table 6 further break down the subsamples by a job's English requirement. The gap reductions across ownership types have similar magnitude whether a

[30] In 2016, the ratio of Chinese enrollment at US higher education institutions to enrollment of bachelor's and graduate students in China is about 2 percent (NBSC, 2017; Institute of International Education, 2017).

job requires English or not, although neither of them are statistically significant due to smaller samples. In addition, English requirement does not seem to explain any observed US-China gap. One cannot reject that the US-China gap is statistically different between jobs require English and jobs that do not.[31]

Second, if the gap reduction across ownership types is driven by culture fitting, the reduction would be smaller among candidates who signal the potential to fit better. While having Chinese work experience may indicate that a candidate knows what is like to work in China, the gap reductions across ownership types have similar magnitude whether candidates have Chinese work experience or not, even though the reductions are not statistically significant due to smaller samples (see Appendix Table A.11).

The two observations above provide suggestive evidence that the firm ownership result reflects the lack of information on American education. However, they do not rule out culture or skill fitting as a potential mechanism in explaining the overall gap in callback rates. There is one additional piece of experimental evidence that also supports the lack of information. Figure 4 and 5 show that the difference in callback rates between applicants in very selective institutions and applicants from inclusive institutions is smaller for US institutions than Chinese institutions. This may indicate that, for example, a Chinese employer finds it difficult to differentiate the University of California-San Diego from Arizona State University, but can easily differentiate Tongji University from Shanghai Lixin University of Accounting and Finance. In Section 5.5, I provide additional evidence on the lack of information and culture fitting using results from the employer survey. For example, it can be difficult and risky to break the tradition for Chinese employers who have never hired US-educated candidates.

If foreign-owned firms have higher posted salaries than Chinese-owned firms, my finding in Section 5.1 that the US-China gap decreases in pay can be driven by firm ownership, or vice versa. Table 7 shows the US-China gap by quartiles of posted salary and by firm ownership. First, note that foreign-owned firms have higher shares of jobs in the bottom two quartiles than in the top two quartiles, so that they do not have higher posted salaries on average. Second, for both Chinese-owned firms (panel A) and foreign-owned firms (panel B), the US-China gap decreases in posted salary. The gap is also smaller for foreign-owned firms within each pay quartile, although none is statistically significant with smaller sample size. Hence, both higher posted salary and foreign ownership are

[31] All Chinese students are required to take one or two national English exams in college to demonstrate that they possess some English skills. Applicants from Chinese institutions in my experiment all state that they have passed the exams.

important in explaining the US-China gap.

Lastly, it is worthwhile to note that firm ownership for target jobs is similar to jobs held by Chinese workers educated abroad. CCG and Zhaopin (2017) reports that about 27 percent of workers educated abroad are at foreign-owned firms, and about 24 percent of firms in the experiment are foreign-owned.

5.3 Selection on unobserved quality

I consider two types of selection that may cause employers in China to associate US degrees with unobserved applicant quality: who studies in the US and who returns. First, college entrance is viewed as highly competitive in China, but the admission process in the US is likely unfamiliar to Chinese employers. Employers may believe that students who study at US institutions are negatively selected. Second, as stated in Section 2.1, all international students are eligible to work short term in the US during summers and after graduation via practical training programs. Employers may associate returning to China with not being able to find employment in the US, and therefore perceive returning students as negatively selected. These two types of selection are similar to what has been studied in the immigration literature regarding who migrates and who returns (e.g., Borjas, 1987; Borjas and Bratsberg, 1996; Chiquiar and Hanson, 2005; Mayr and Peri, 2008; Grogger and Hanson, 2011; Abramitzky et al., 2012).

I test whether employers view applicants with an American education as negatively selected prior to college by randomly varying signals of pre-college credentials on job applications. Table 8 presents the results using two different signals. Columns 1 examines whether signaling graduation from a local elite high school on resumes changes the US-China gap in callback rates. About 28 percent of the applicants are assigned a local elite high school, and the rest list no high school on their resumes. This is consistent with the fact that in practice, only elite high schools are observed in the bank of real resumes. As discussed in Section 4, graduation from an elite high school mostly signal to employers an applicant's ability to attend a four-year college in China, with perhaps a higher probability of attending a selective one. This signal does not add much information on quality of applicants who have attended a Chinese college, because students from all high schools take the same entrance exam.

Column 2 examines whether signaling a test score on China's college entrance exam alters the US-China gap. In the spring job season, one of the two US-educated applicants applying for the same job is assigned a test score that is high enough to get into an average, very selective, or selective school in the sample. These test scores signal to employers an applicant's ability to attend a high-quality college in China. Column 3 provides a robustness check by including both types of signals. Appendix C provides details of the high school selection and test score construction.

Evidence from Table 8 shows that controlling for pre-college credentials does not decrease the US-China gap in callback rates, contradicting a perceived negative selection on who studies in the US. Signaling an elite local high school on resumes (relative to listing no high school) decreases the US-China gap modestly, by 0.8 percentage point, but the decrease is not statistically significant. Signaling a high score on China's college entrance exam also does not change the US-China gap. Note that both types of signals provide additional information on applicant quality only if a US institution is perceived as selecting worse students from high schools than Chinese institutions.

When callback rates do not vary by a resume characteristic, a concern for all audit studies is that such a characteristic is not salient to employers. It is possible that signals of pre-college credentials are neither noticed nor valued by employers in China. My study design tries to minimize this concern by listing the signals of pre-college credentials right below an applicant's college education, which is found to influence employer decisions on callbacks. The two signals of pre-college credentials have tried to maximize what one can reasonably signal on a resume.

Two alternative sources provide evidence consistent with no perceived negative selection on who studies in the US. First, Chen et al. (2020) document that Chinese students who take the SAT and enrolled in US colleges are from the top of their high school class. They also have higher SAT scores than their peers at US institutions. Second, Figure 3 shows that my sample US and Chinese institutions enroll students from similar parts of the distributions for test scores, despite being based on different exams. The employer survey also provide additional evidence and the results are discussed in Section 5.5.

I test whether there is a perceived negative selection on who returns to China by randomly varying whether applicants with US degrees have had work experience in the US. These results are presented in columns 1 and 2 of Table 9. Furthermore, since work experience may become increasingly more important after students have left school, I examine the role of US work experience separately for applicants who have graduated. Columns 3 and 4 present results on US-China callback gaps across two employment statuses for applicants with US degrees: (1) college graduates who have returned to work full time in China and (2) college graduates who have stayed to work full time in the US (via OPT). Columns 5 and 6 further break down applicants who have returned into two subsamples: those who have had US internship experience and those have had similar experience in China.

The results from Table 9 suggest that employers do not perceive returning students as negatively selected; having been employed in the US does not help to close the US-China gap. While US work experience may also signal potentially better outside options in the US, it does not decrease the gap, even among those who have returned to work full time in China.[32] Given that 84 percent of Chinese students who completed their studies abroad had returned to China by 2017, this is consistent with the idea that employers may simply view returning as a general trend instead of a selection on quality.[33] Most returning students were born under China's one-child policy, and a survey shows that 70 percent of students educated abroad indicate that "unite with family" is their reason for returning (CCG and Zhaopin, 2017).

Evidence presented in this section so far suggests that perceived negative selection on who studies in the US and who returns does not explain the US-China gap in callback rates. This is consistent with the finding in Section 5.1 that the gap is the smallest at high-quality jobs, which works against any type of perceived negative selection on applicant quality. Lastly, it is important to note that employers may look for a much broader set of skills than academic ability. Even if there is negative selection on test scores, either before or after college, it does not necessarily influence employers' callback decisions, since students may have acquired other valuable skills in college.

5.4 Local employer network

One advantage Chinese institutions may have over US institutions is better access to local employer networks. Since Chinese institutions in my main experimental sample are in the same city as the target jobs, better local employer networks may drive the detected US-China gap in callback rates.

To test this hypothesis, I conduct a supplementary experiment in which I decrease potential access to local employer networks for sample Chinese institutions. Specifically,

[32]This finding is broadly consistent with Abarcar (2015), who finds that employers in the Philippines do not value migrant workers' foreign work experiences.

[33]Note that potential selection on not going to graduate school is unlikely a concern. First, the share of Chinese students in the US who go to graduate school is similar to that of college graduates in China (see Appendix B). Second, I do not consider jobs that require a master's degree. For target jobs, I purchased data on applicant composition by educational level. Only about 8 percent of applications have a master's degree.

I sent 1,084 applications to business job vacancies in Guangzhou, the third largest city in China. This supplementary sample follows the same design as the main experiment and uses the same set of schools. Hence, employers in Guangzhou compare the same set of US institutions with the same set of Chinese institutions as employers in Beijing and Shanghai. Assuming that sample Chinese institutions have a weaker employer network in Guangzhou, the US-China gap would decrease if a local employer network is important.

Guangzhou is an ideal setting for this empirical test for two reasons. First, Guangzhou employers are unlikely to be concerned about selection on who leaves Guangzhou for college and who returns to work. Compared to Beijing and Shanghai, Guangzhou has a smaller supply of colleges relative to its population.[34] It is common for high school graduates in Guangzhou to go to college elsewhere and later return. Second, Guangzhou is among the most popular destination cities for college graduates in China and returning overseas students (Zhaopin, 2017; CCG and Zhaopin, 2017). Employers in Guangzhou are likely to have a similar amount of information on both Chinese and US institutions in the sample as employers in Beijing and Shanghai.

Table 10 shows that the US-China gap in callback rates persists in Guangzhou. Applicants from US institutions are 27 percent (6 percentage points) less likely to receive a callback than applicants from institutions in China. Even though the sample size is much smaller than the main experimental sample, the US-China gap is statistically significant at 1 percent. The gap is larger than for business jobs in the main experimental sample, but is not statistically significant. This result is not driven by either higher posted pay or foreign-owned firms, as target jobs in Guangzhou have lower posted pay on average and the foreign-owned firm share is much smaller. While this result is inconsistent with the hypothesis that the US-China gap is driven by access to better local employer networks, it does not rule out the possibility of a better employer network at the national level for Chinese institutions.

5.5 Evidence from the employer survey

The employer survey is designed to shed further light on potential mechanisms by directly asking hiring managers the reasons for their decisions after the survey-based choice experiments. The survey results are thoroughly consistent with the lessons from the field experiment and offer additional insights. The results presented in this section are

[34]For example, while Guangzhou had more high school graduates than Beijing in 2016, it only has two very selective colleges and two selective colleges (NBSC, 2017; Guangzhou Bureau of Statistics, 2017).

based on complete responses from 507 hiring managers.

As detailed in Section 3.4, the choice experiments ask hiring managers to choose one of two otherwise-identical candidates from different college institutions for a job interview. Each hiring manager is presented the choice experiment three times with different US-China pairs of institutions. Candidates from Chinese institutions are chosen 80 percent of the time over candidates from US institutions, implying a US-China gap in interview rates of -60 percentage points.[35] Column 1 of Table 11 shows the gap under the regression framework characterized by equation (1), where the dependent variable is whether a candidate is selected for an interview. Column 2 shows the difference is robust after including hiring manager fixed effects as a randomization check.

Following the choice experiments, hiring managers are asked to go through 10 potential reasons (including a customizable text-entry) for making their interview decisions and to pick the most important one. Table 12 presents shares of each reason that is picked when a Chinese institution is chosen over a US institution by hiring managers, and Appendix Table A.12 presents the shares when a US institution is chosen over a Chinese institution. The original survey lines are in quotes and the bold texts rephrase the survey lines using the terminology that was presented in the earlier discussions on mechanisms.

Three important results can be observed. First, mechanisms that are inconsistent with the field experiment data are also not chosen by large shares of hiring managers as their top reason for preferring Chinese institutions. Table 12 shows that concerns over negative selection of who studies in the US and who returns to China are picked as the most important reason under 10 percent of the time, and a strong employer network is picked less than 4 percent of the time. Part 3 of the survey also asks employers' general attitudes towards returning students. About 31 percent of hiring managers disagree with the statement that returning students have low ability and cannot find a job in the US, in contrast to 13 percent who agree and the rest who are not sure.

Second, mechanisms that are consistent with the field experiment data are also quite evident in the survey. Table 12 shows that 35 percent of the time hiring managers pick reasons for the fear of better outside options, with half of the 35 percent fearing US-educated candidates are more likely to quit, a quarter fearing they are more likely to take other jobs, and a quarter fearing they are overqualified.[36]

[35] The gap is much larger than the field experiment because the survey intentionally forced employers to make a single choice between a US school and a Chinese school. I designed the survey in this way to create more variation in anticipation of a small sample size.

[36] When hiring managers choose US institutions over Chinese institutions, they also tend to choose the fear

The survey results also show that a lack of information on American education is very relevant to employers' interview decisions. Hiring managers are asked to rate their knowledge of undergraduate educational quality for each institution listed in the vignettes. The ratings range from one (do not know anything) to five (very knowledgable). Figure 6 plots the distribution of knowledge ratings by the country of the institution, and it is clear that hiring managers know much less about US universities relative to Chinese universities. For each pair of institutions from which hiring managers make an interview decision, I compute the US-China knowledge gap as the difference in knowledge ratings. I interact this measure of knowledge gap with the US degree indicator to test whether employers are more likely to choose a US-educated candidate when they know more about the American institution. Column 3 of Table 11 shows that every one point increase in the knowledge of US schools relative to Chinese schools is associated with a 18.2 percentage points decrease of the interview gap.

Furthermore, hiring managers do not have much experience in hiring US-educated candidates; only 31 percent of them indicate that their company has hired workers with an American education in the last two years. Column 4 of Table 11 shows that when companies have recent hiring experience with US-educated workers, the interview gap closes by 27.3 percentage points. Column 5 shows that the gap decreases in both knowledge about US institutions and having hiring experience. Evidence from column 3-5 of Table 11 is consistent with the lack of information channel discussed in Section 5.2.

Third, the survey sheds light on mechanisms that are hard to test using the field experiment data. Table 12 shows that close to 35 percent of the time, concerns about a candidate's cultural fit is the most important reason that hiring managers choose Chinese institutions over US institutions. In contrast, hiring managers generally do not report better education at Chinese institutions as the key reason (less than 8 percent).

6 Conclusion

US higher education has attracted millions of international students to make human capital investment, and institutions in the US benefit greatly from these investments, both financially and intellectually. However, little is known about the value of an American education in labor markets outside the US In this paper, I conduct a large-scale field experiment to study the question of how employers in China value US college degrees

of better outside options as their top reason (Appendix Table A.12). These results highlight the importance of job seekers' outside options when employers make hiring decisions.

relative to domestic degrees. I also conducted a large employer survey with vignette choice experiments to cross validate the field experiment and further probe mechanisms.

This paper finds that the average employer in China for returning Chinese students do not prefer US-educated candidates over Chinese-educated candidates when making job interview offers. Even for jobs with higher posted salaries and at multinational firms, the US-China gap in callback rates are not positive. Given the high cost of studying in the US relative to a college education in China, findings from this paper suggest that some non-labor market reasons can be quite important in driving *marginal* students' decisions on where to invest human capital.

The importance of non-labor market benefits, such as consumption value (e.g., enjoyment of foreign cultures and school prestige), is consistent with recent findings that college amenities are important to students in the US when making college decisions (Jacob et al., 2018). Attending US institutions also provides a pathway to immigration. A recent survey of overseas Chinese students asked why they seek undergraduate degrees abroad (China Citic Bank and Nielsen, 2015). While "improve labor market competitiveness" is the most popular choice (63 percent), other reasons include "experience foreign cultures" (61 percent), "scholarly pursuits" (57 percent), "work abroad" (35 percent), and "help immigration" (23 percent).

Labor market values can still play an important role in students' education decisions. This paper does not measure the value of a US college education outside the Chinese labor markets. For example, despite the small probability of being able to work in the US after graduation, the potential income for college graduates is much higher than it is in China. Based on administrative data on H-1B work visas, the median income in 2017 for Chinese nationals with a US undergraduate degree is \$65,000—higher than the median of target jobs or jobs held by returning Chinese students, \$24,300 (PPP adjusted). Kato and Sparber (2013) find that declines in the availability of work visas decrease the number of college applications from international students.[37] Additionally, this paper only measures the labor market value in getting callbacks/interview offers. While the employer survey from this paper suggests US-educated candidates are unlikely to outperform domestic students for actual interviews, it is possible that US education has larger long-term value in one's career or has a higher return for a special set of jobs.

[37] Relatedly, Rosenzweig (2006) find that international student flow is consistent with high returns to skills in the US rather than a low college supply in the home country. Note that the composition of international students has changed drastically since their period of study. Few Chinese students were studying at US undergraduate institutions in early 2000.

It is possible that Chinese students are misinformed about the value of a US education in Chinese labor markets. A recent survey shows that about 70 percent of returning Chinese students indicate that their salaries are below expectations, and only 1 percent respond above expectation (CCG and Zhaopin, 2017). Research find that students are poorly informed about labor market returns to college education in their own country (Wiswall and Zafar, 2014; Hastings et al., 2015). This could also be true internationally. Since attending elite institutions in China has large wage returns (Jia and Li, 2017), Chinese students and families are likely to associate highly prestigious US institutions with large labor market benefits. Additionally, China has a large industry profiting by assisting students to apply for US universities. This industry is often the source of information for US higher education and it has more interest in advertising benefits of an American education. A potentially interesting question for future research is to explore to what extent reasons such as consumption value matter and whether a lack of information plays a role in students' (or families') decisions on whether to invest in human capital abroad.

Lastly, an important policy implication of my findings is that US institutions may want to help students transition from an American education to a Chinese workplace. China is the largest source country of foreign students in the US, and accounts for 93 percent of the growth in the last decade. Hence, investing in career services can be important for schools that heavily benefit from these students. One possibility would be to advertise US schools in Chinese labor markets to reduce potential information frictions. Schools may also provide students with more information about their job prospects in China, and help them better navigate the job search process. Specifically, they may want to prevent students from leaving an impression with employers of being "too high to reach."

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Figures and tables

Figure 1: Experimental design

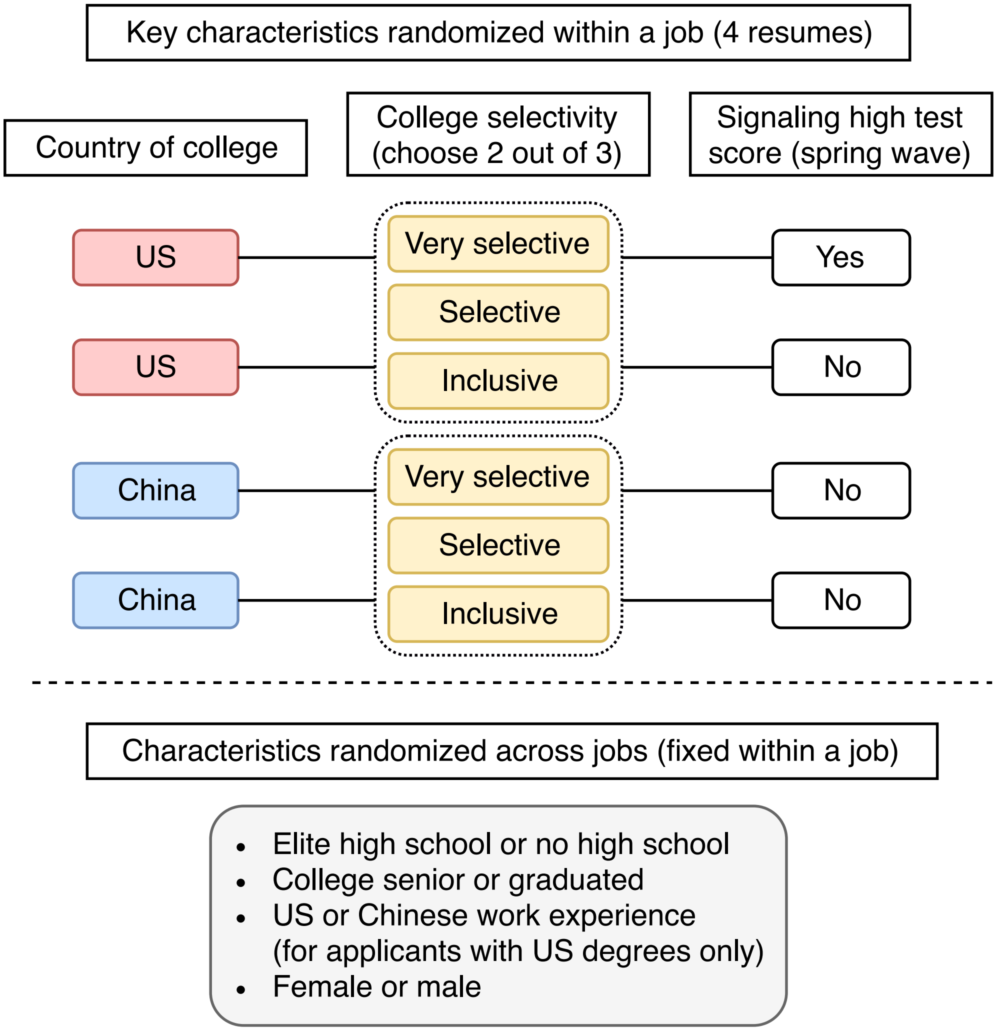
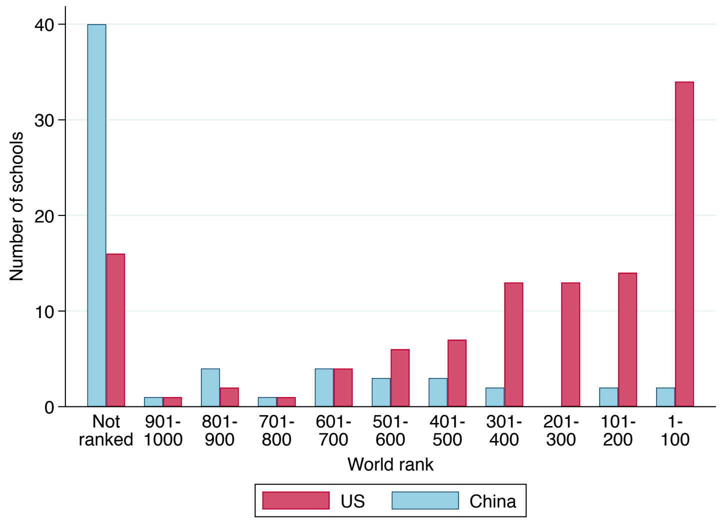
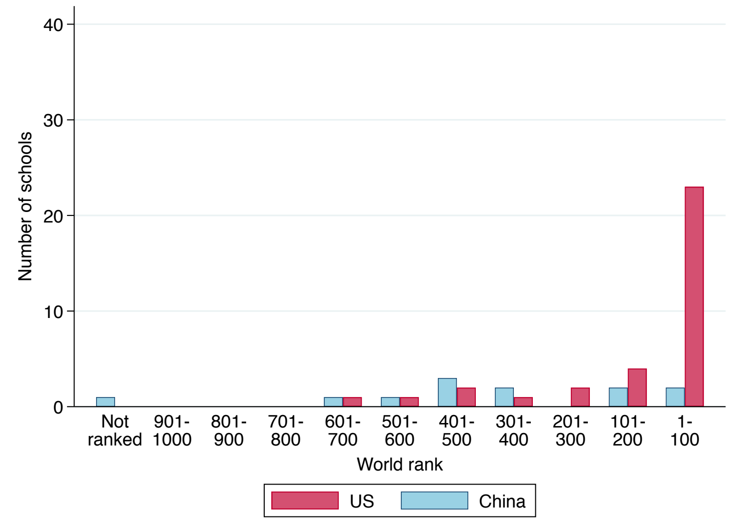


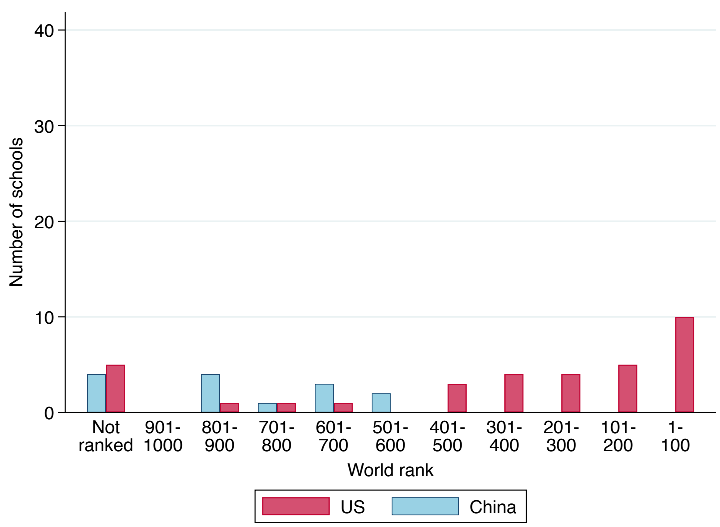
Figure 2: Distribution of world rankings for sample institutions by country



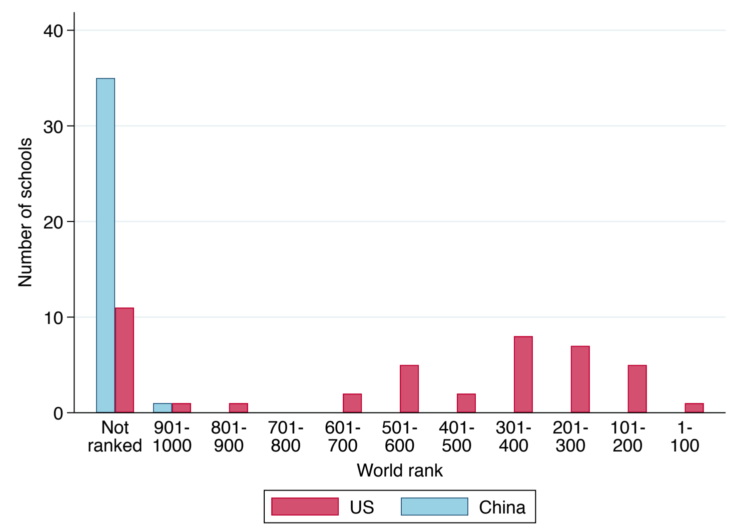
(a) All sample institutions



(b) Very selective institutions



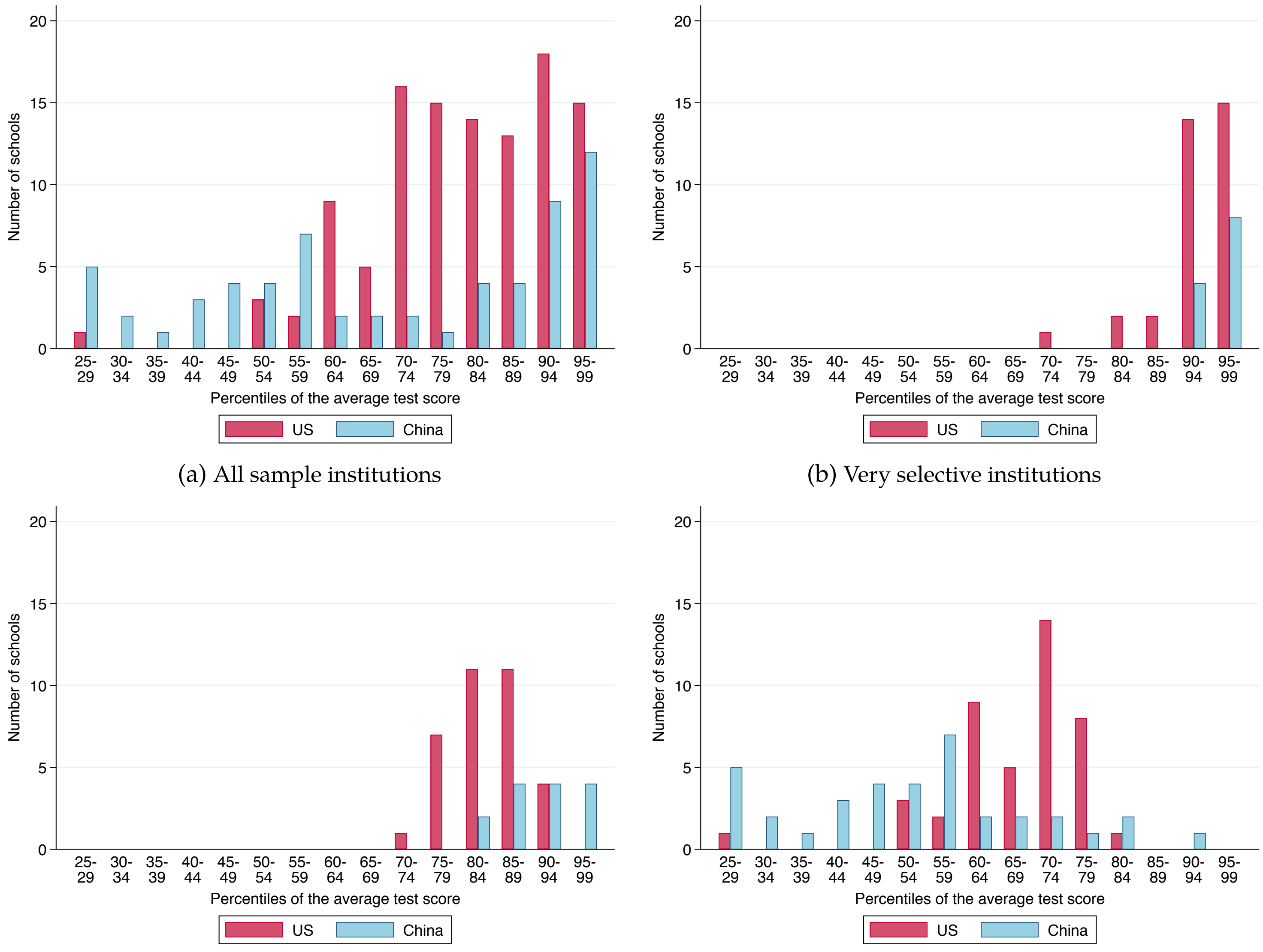
(c) Selective institutions



(d) Inclusive institutions

Note: Author's calculations using world rankings from the 2018 US News Best Global Universities.

Figure 3: Distribution of average test score percentiles for sample institutions by country



(a) All sample institutions

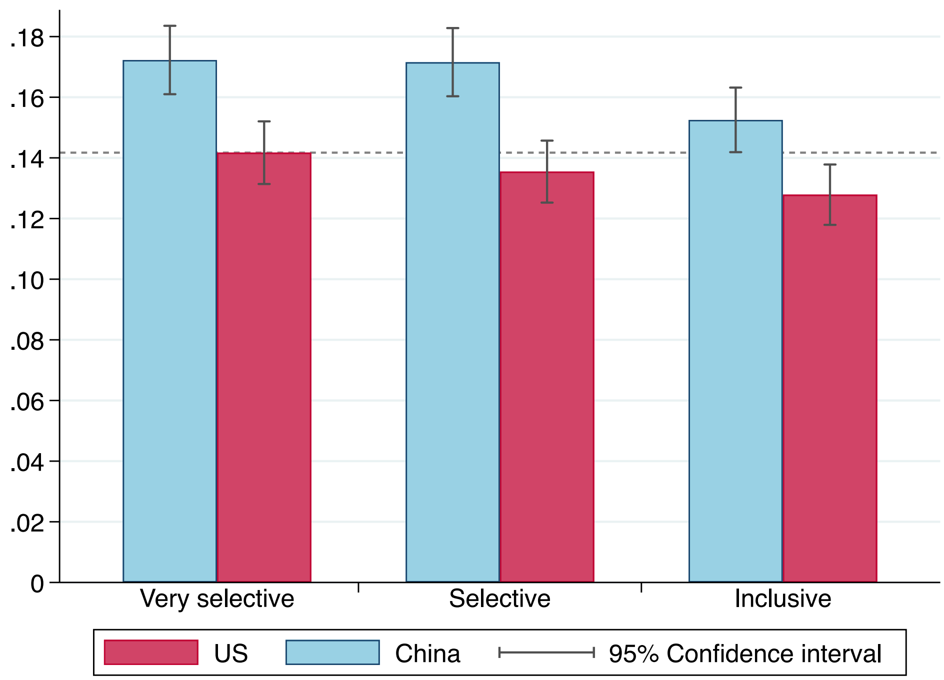
(b) Very selective institutions

(c) Selective institutions

(d) Inclusive institutions

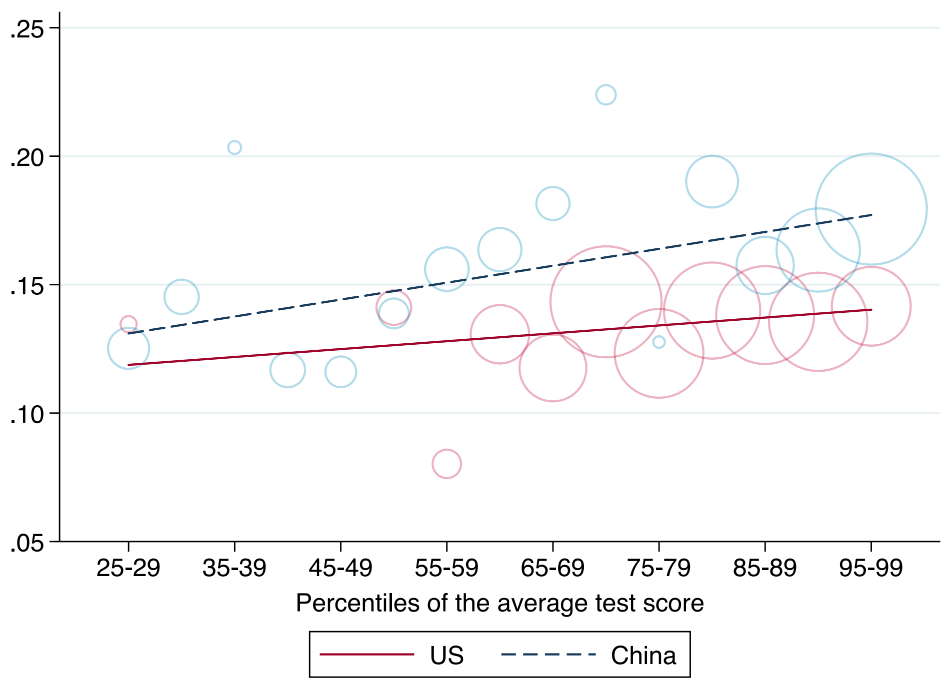
Note: Author's calculations using test score data for the entering class in the fall of 2017. Data for US institutions are from US News' Academic Insights database. Data for Chinese institutions are collected from gaokao.chsi.com.cn, the official college admissions website referenced by China's Ministry of Education. See details of test score percentile calculations in Appendix B.

Figure 4: Callback rates by selectivity groups of institutions



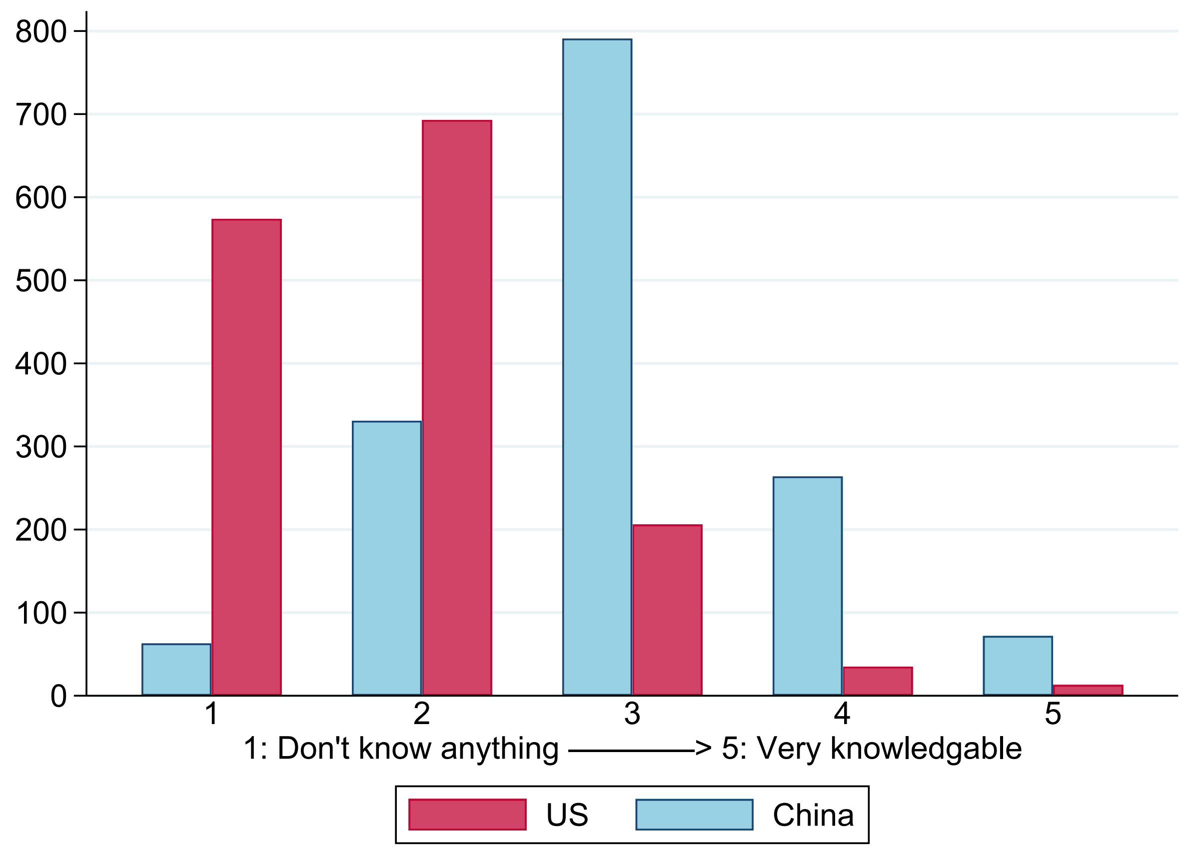
Note: The callback rate is the share of resumes that received a personalized positive contact from a potential employer via phone, email, or text message. Mean callback rates by country-selectivity group and their 95 percent confidence intervals are plotted. The dotted horizontal line reflects the mean callback rate for very selective US institutions. The figure uses data from the main analysis sample containing 26,036 job applications submitted to business and computer science postings in Beijing and Shanghai. See these estimates under a regression framework in Appendix Table A.6.

Figure 5: Callback rates by percentiles of the average test score for enrolled students



Note: Percentiles of the average test score are for the entering class in the fall of 2017. The callback rate is the share of resumes that received a personalized positive contact from a potential employer via phone, email, or text message. The average callback rate is computed for each test score percentile bin. Straight lines are linear fits to the circles, which are weighted by the sample size of each percentile bin in the experiment. See details of test score percentile calculations in Appendix B.

Figure 6: Distribution of hiring managers' self-rated knowledge of undergraduate education quality for institutions listed in the employer survey's choice experiment



Notes: The employer survey asks hiring managers to choose between two other-wise candidates except their undergraduate institutions to offer an interview. Each hiring manager is asked to make this decision three times for three different set of schools. Each hiring manager is also asked to rate their knowledge of the undergraduate education quality for every institution. This figure contains data on 3,042 knowledge ratings made by 507 hiring managers.

Table 1: Programs and occupations

Occupation category (1)	Degree programs (2)	Sample job titles (3)	Share of all full-time vacancies (4)
Business			
Accounting/finance/ banking/sales/customer service/marketing	Accounting, finance, economics, marketing, business administration	Accountant, billing/payroll spec, business assoc, financial analyst, project assistant, sales assoc, account manager, marketing spec	0.315
Computer science			
Software/network/IT	Computer science	Web developer, software engineer, testing engineer	0.191

Note: Occupation categories and degree programs are based on Classification of Instructional Programs (CIP) codes, and occupations are consistent with occupations listed on the online job board. Sample job titles are the most common titles from the jobs applied for in the experiment. The share of all full-time vacancies is the number of full-time job vacancies requiring a bachelor's degree posted in the last 24 hours for a given occupation divided by the total number of full-time job vacancies requiring a bachelor's degree posted in the same period. I calculate this share for three consecutive days in December 2017 and take the average. Shares are robust when using the same data collected in September 2017 and April 2018.

Table 2: Summary Statistics

	Callback rates	Resumes
Total	0.150	26,036
By country of college		
US	0.135	13,018
China	0.165	13,018
By college selectivity groups		
Very selective	0.157	8,689
Selective	0.154	8,636
Inclusive	0.140	8,711
By city		
Beijing	0.138	12,676
Shanghai	0.162	13,360
By occupation		
Business	0.176	19,108
Computer science	0.078	6,928
By job season		
Fall	0.134	11,340
Spring	0.163	14,696
By gender		
Female	0.166	12,628
Male	0.136	13,408
By work status		
College senior	0.162	12,340
Working full-time	0.139	13,696
By signal of elite high school		
Signal	0.147	7,212
No signal	0.151	18,824
By quartiles of posted salary		
Below 25th percentile	0.194	6,296
25th-50th percentile	0.181	3,224
50th-75th percentile	0.147	9,896
Above 75th percentile	0.098	6,620
By firm ownership		
Foreign-owned	0.157	6,096
Chinese-owned	0.148	19,940

Notes: The callback rate is the share of resumes that received a personalized positive contact from a potential employer. Data contain applications sent to jobs in Beijing and Shanghai.

Table 3: Callback regressions by occupation

	All (1)	All (2)	All (3)	Business (4)	CS (5)
US degree	-0.030^{***}	-0.030^{***}	-0.030^{***}	-0.032^{***}	-0.026^{***}
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)
Working full time		-0.023^{**}			
		(0.010)			
Female		0.030^{***}			
		(0.007)			
Spring job season		0.029^{***}			
		(0.007)			
China callback rate	0.165	0.165	0.165	0.192	0.091
Observations	26,036	26,036	26,036	19,108	6,928
F(labor markets)		0.000			
F(statement)		0.922	0.919	0.906	0.618
F(names)			0.759	0.730	0.511
Vacancy FE			Yes	Yes	Yes

Notes: The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Degrees from China is the omitted education category. Column 2 includes fixed effects for self-statement templates and labor markets, where each labor market is a city-occupation pair. Columns 3-5 include fixed effects for names and self-statement templates. p-values are reported for F-tests that these fixed effects are zero. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table 4: Callback regressions by posted salary quartiles

		Quartiles of posted salary			
	All (1)	Below 25th percentile (2)	25th-50th percentile (3)	50th-75th percentile (4)	Above 75th percentile (5)
US degree	−0.065***	−0.058***	−0.039***	−0.023***	−0.010*
	(0.007)	(0.007)	(0.010)	(0.006)	(0.006)
× salary (in $1,000s)	0.002***				
	(0.000)				
China callback rate	0.165	0.223	0.201	0.159	0.103
Observations	26,036	6,296	3,224	9,896	6,620
US degree diff wrt (2)			0.019	0.035***	0.048***
			(0.012)	(0.009)	(0.009)
Vacancy FE	Yes	Yes	Yes	Yes	Yes

Notes: Salaries are proxied by the midpoint of the posted salary. The median salary is 84,000 RMB or $12,945. The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Degrees from China is the omitted education category. All columns include fixed effects for names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table 5: Callback regressions by employment status of applicants with US degrees

	Returned to work in China (1)	Stayed to work in US (2)	Returning to work in China (3)
US degree	-0.020^{***}	-0.033^{***}	-0.035^{***}
	(0.006)	(0.006)	(0.005)
China callback rate	0.153	0.152	0.180
Observations	6,844	6,852	12,340
US degree diff wrt (1)		-0.013	-0.015^{*}
		(0.009)	(0.008)
Vacancy FE	Yes	Yes	Yes

Notes: The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Degrees from China is the omitted education category. All columns include fixed effects for names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table 6: Callback regressions by firm ownership and job English requirement

			Require English		Require no English	
	Chinese	Foreign	Chinese	Foreign	Chinese	Foreign
	(1)	(2)	(3)	(4)	(5)	(6)
US degree	-0.034^{***}	-0.018^{***}	-0.034^{***}	-0.015	-0.034^{***}	-0.020^{**}
	(0.004)	(0.007)	(0.010)	(0.012)	(0.004)	(0.008)
China callback rate	0.165	0.166	0.194	0.181	0.159	0.157
Observations	19,940	6,096	3,596	2,416	16,344	3,680
US degree diff wrt the first col within group		0.016^{**}		0.018		0.014
		(0.008)		(0.015)		(0.009)
Vacancy FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Foreign-owned firms include firms owned by regions outside of China and joint ventures. Jobs requiring English mention English as a skill in their vacancy posts. Degrees from China is the omitted education category. All columns include fixed effects for names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table 7: Callback regressions by posted salary quartiles and firm ownership

	Below 25th percentile (1)	25th-50th percentile (2)	50th-75th percentile (3)	Above 75th percentile (4)
Panel A: Chinese-owned firms				
US degree	-0.063^{***}	-0.047^{***}	-0.026^{***}	-0.015^{**}
	(0.009)	(0.012)	(0.006)	(0.006)
China callback rate	0.227	0.214	0.158	0.101
Observations	4,620	2,376	7,576	5,368
US degree diff wrt (1)		0.017	0.038^{***}	0.049^{***}
		(0.015)	(0.011)	(0.011)
Panel B: Foreign-owned firms				
US degree	-0.043^{***}	-0.021	-0.017	0.008
	(0.013)	(0.017)	(0.012)	(0.014)
China callback rate	0.211	0.165	0.164	0.112
Observations	1,676	848	2,320	1,252
US degree diff wrt (1)		0.023	0.027	0.052^{***}
		(0.021)	(0.018)	(0.019)
Panel diff in US degree	0.020	0.026	0.009	0.023
	(0.016)	(0.020)	(0.013)	(0.015)
Share of foreign-owned firms in each quartile	0.266	0.263	0.234	0.189

Notes: Salaries are proxied by the midpoint of the posted salary. The median salary is 84,000 RMB, or $12,945. The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Foreign-owned firms include firms owned by regions outside of China and joint ventures. Degrees from China is the omitted education category. All columns include fixed effects for vacancies, names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table 8: Callback regressions by signals of pre-college credentials

	Elite HS (1)	Test (2)	Both (3)
US degree	-0.032^{***}	-0.030^{***}	-0.032^{***}
	(0.004)	(0.004)	(0.004)
$\times$ Signal elite high school	0.008		0.008
	(0.007)		(0.007)
$\times$ Signal high test score		-0.002	-0.002
		(0.005)	(0.005)
China callback rate	0.165	0.165	0.165
Observations	26,036	26,036	26,036
Vacancy FE	Yes	Yes	Yes

Notes: The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Degrees from China is the omitted education category. All columns include fixed effects for names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table 9: Callback regressions by US work experience for applicants with US degrees

	Any US work exp		Returned to CN	
	No	Yes	CN exp	US exp
	(1)	(2)	(3)	(4)
US degree	-0.026^{***}	-0.032^{***}	-0.018^{**}	-0.023^{***}
	(0.006)	(0.004)	(0.009)	(0.009)
China callback rate	0.169	0.156	0.150	0.156
Observations	7,164	18,872	3,404	3,440
US degree diff wrt the first col within group		-0.005		-0.005
		(0.007)		(0.012)
Vacancy FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Degrees from China is the omitted education category. All columns include fixed effects for names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table 10: Callback regressions by experimental samples (business jobs)

	Main (1)	Guangzhou Supplementary (2)
US degree	-0.032^{***}	-0.058^{***}
	(0.004)	(0.018)
China callback rate	0.192	0.245
Observations	19,108	1,084
US degree diff wrt (1)		-0.026
		(0.018)
Vacancy FE	Yes	Yes

Notes: The main sample contains job applications submitted to business postings in Beijing and Shanghai. The supplementary sample contains job applications submitted to business postings in Guangzhou. It follows the same design as the main experiment but uses institutions in Beijing and Shanghai to apply for jobs in Guangzhou. The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Degrees from China is the omitted education category. All columns include fixed effects for names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table 11: Interview regression from the employer survey's choice experiment

	Interview (1)	Interview (2)	Interview (3)	Interview (4)	Interview (5)
US degree	-0.606^{***}	-0.606^{***}	-0.398^{***}	-0.691^{***}	-0.481^{***}
	(0.025)	(0.025)	(0.036)	(0.028)	(0.038)
× US-China knowledge gap			0.182^{***}		0.178^{***}
			(0.015)		(0.015)
× Hired US-educated before				0.273^{***}	0.249^{***}
				(0.057)	(0.054)
China interview rate	0.803	0.803	0.803	0.803	0.803
Observations	3,042	3,042	3,042	3,042	3,042
Hiring manager FE	No	Yes	Yes	Yes	Yes

Notes: The dependent variable is an indicator for being chosen to offer an interview by hiring managers in the survey's choice experiment. Degrees from China is the omitted education category. US-China knowledge gap is the difference between hiring managers' knowledge of the US institution and Chinese institution. Hired US-educated before indicate that the company has hired US-educated workers in the last two years. There are total of 260 hiring managers in the data. Standard errors are clustered at the hiring manager level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table 12: The most important reason for hiring managers choosing a Chinese university over a US university in the employer survey

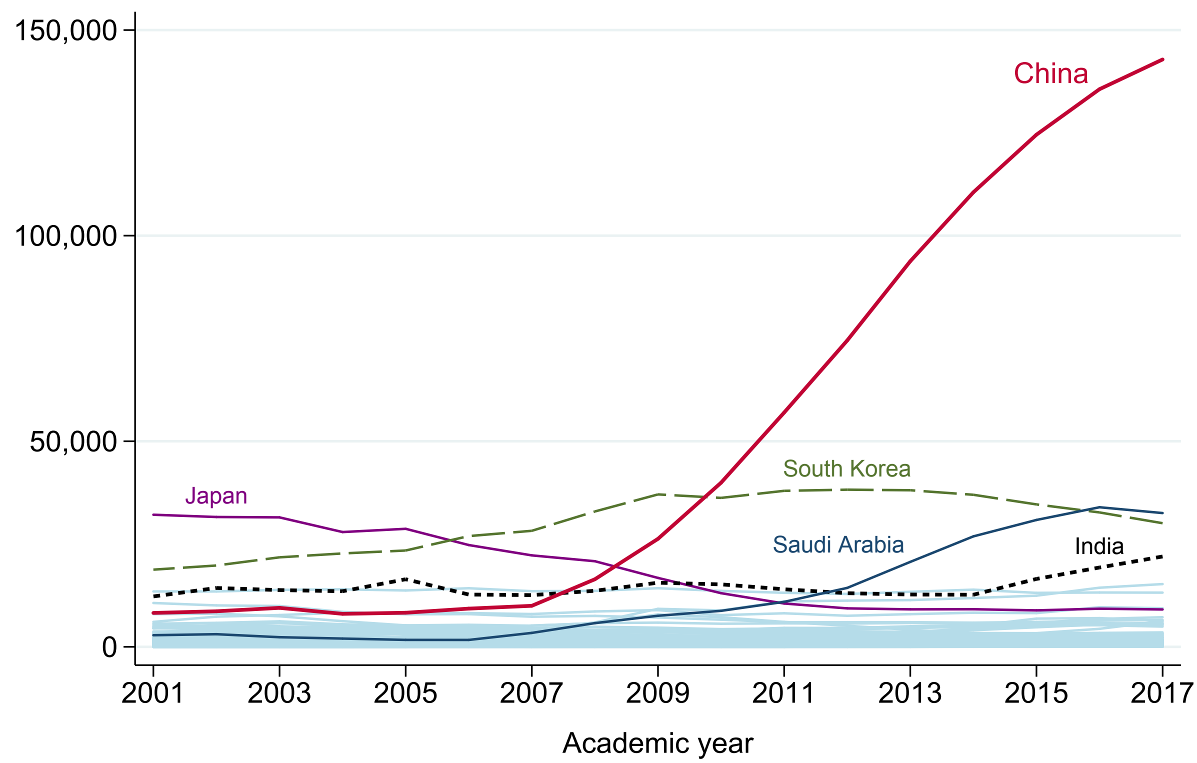
	Share chosen
US-educated candidates have better outside options	**0.349**
"Students from the unselected school are overqualified for the job"	0.086
"Students from the unselected school are more likely to take other jobs"	0.091
"Students from the unselected school are more likely to quit"	0.173
Negative selection of who studies at the US institution	**0.064**
"Students admitted to the selected school are better"	
Negative selection of who returns from the US institution	**0.035**
"Students from the unselected school applying for the job are worse than the average at their school"	
Chinese schools have better employer network	**0.039**
"The selected school has a strong connection with the company"	
Students from Chinese schools fit firm culture more	**0.344**
"Students from the selected school are more likely to suit the company's work culture"	
Chinese schools provide better education	**0.079**
"The selected school provides a better college education"	
Students from Chinese schools have better English	**0.034**
"Students from the selected school have better English skill needed for the job"	
Others	**0.055**
"If other, please specify"	

Notes: The employer survey asks hiring managers to choose between two other-wise candidates except their undergraduate institutions to offer an interview. Each hiring managers is asked to make this decision three times for three different set of schools. Among 1,521 decisions made by 507 hiring managers, 80.28 percent offered candidates educated in China an interview instead of candidates educated in the US. While 94.87 percent of hiring managers offered an interview to Chinese-educated candidates at least once, 40.43 percent offered US-educated candidates at least once. Following each question on whom to offer an interview, hiring managers are asked to select the most important reason for making the interview decision. Ten reasons are listed and respondents can enter their own texts. The quoted texts in the table are what shown to the employers and the texts in bold indicate the targeted mechanisms of the quoted texts.

ONLINE APPENDIX, NOT FOR PUBLICATION

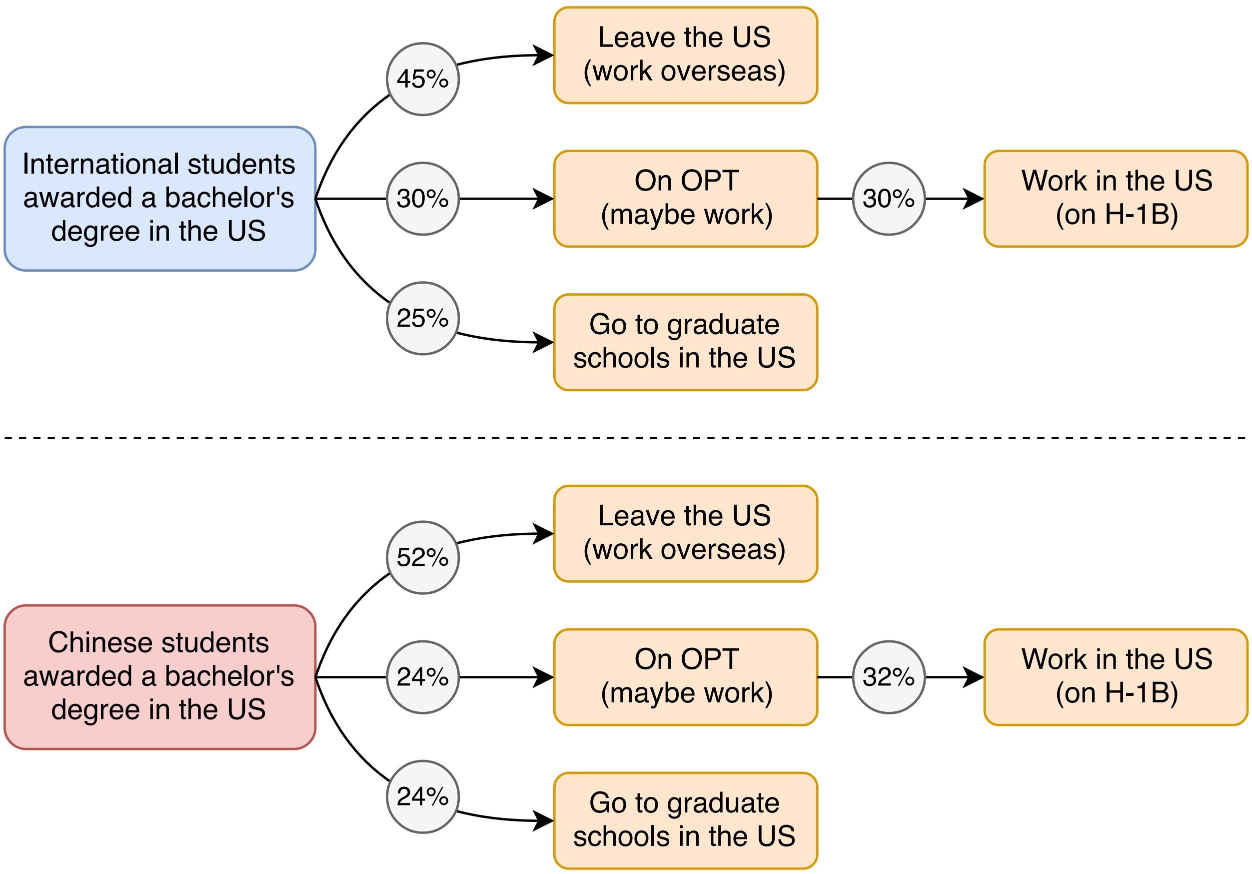
A Appendix figures and tables

Figure A.1: International undergraduate enrollment in the US by country



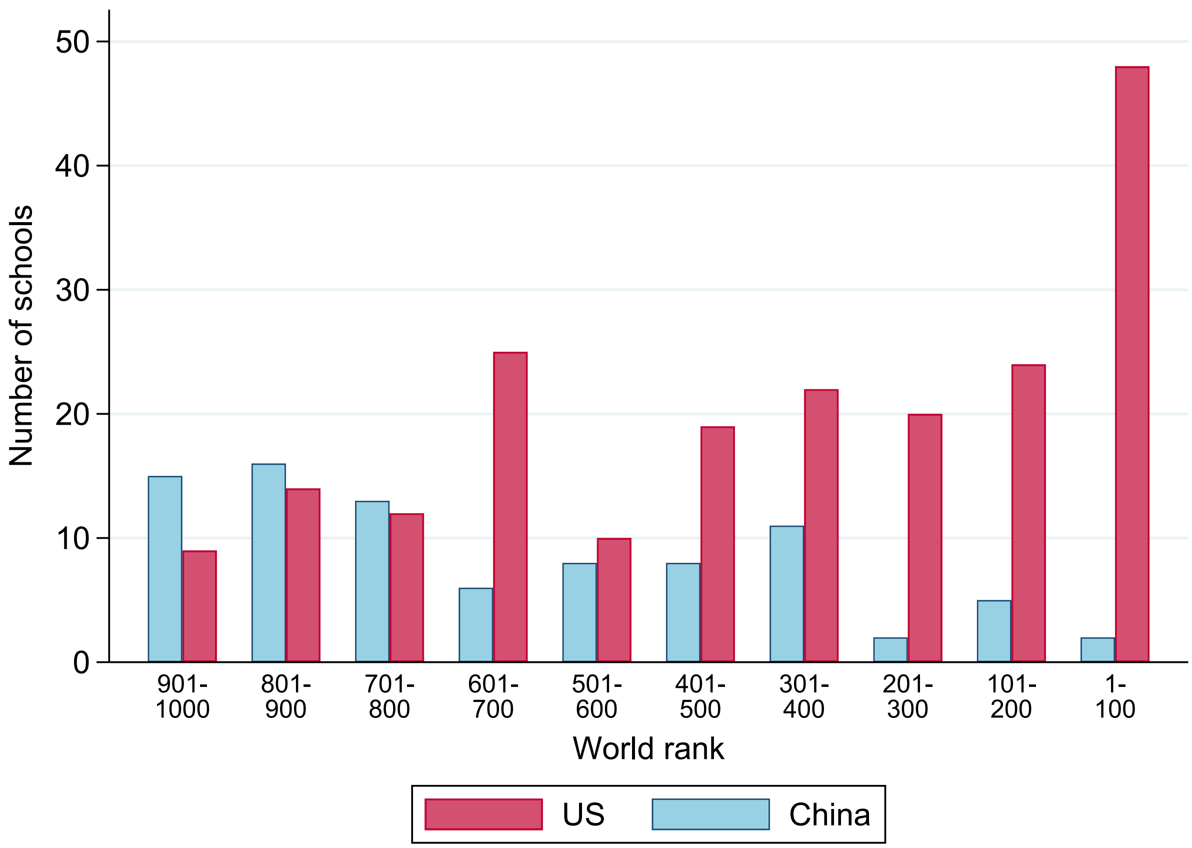
Note: Data include 176 regions for the period of 2000/01 to 2016/17 academic years and are obtained from the Institute of International Education at: https://www.iie.org/Research-and-Insights/Open-Doors/Data.

Figure A.2: Estimated transition probabilities for international/Chinese students who received bachelor's degrees in the US, 2015 and 2016



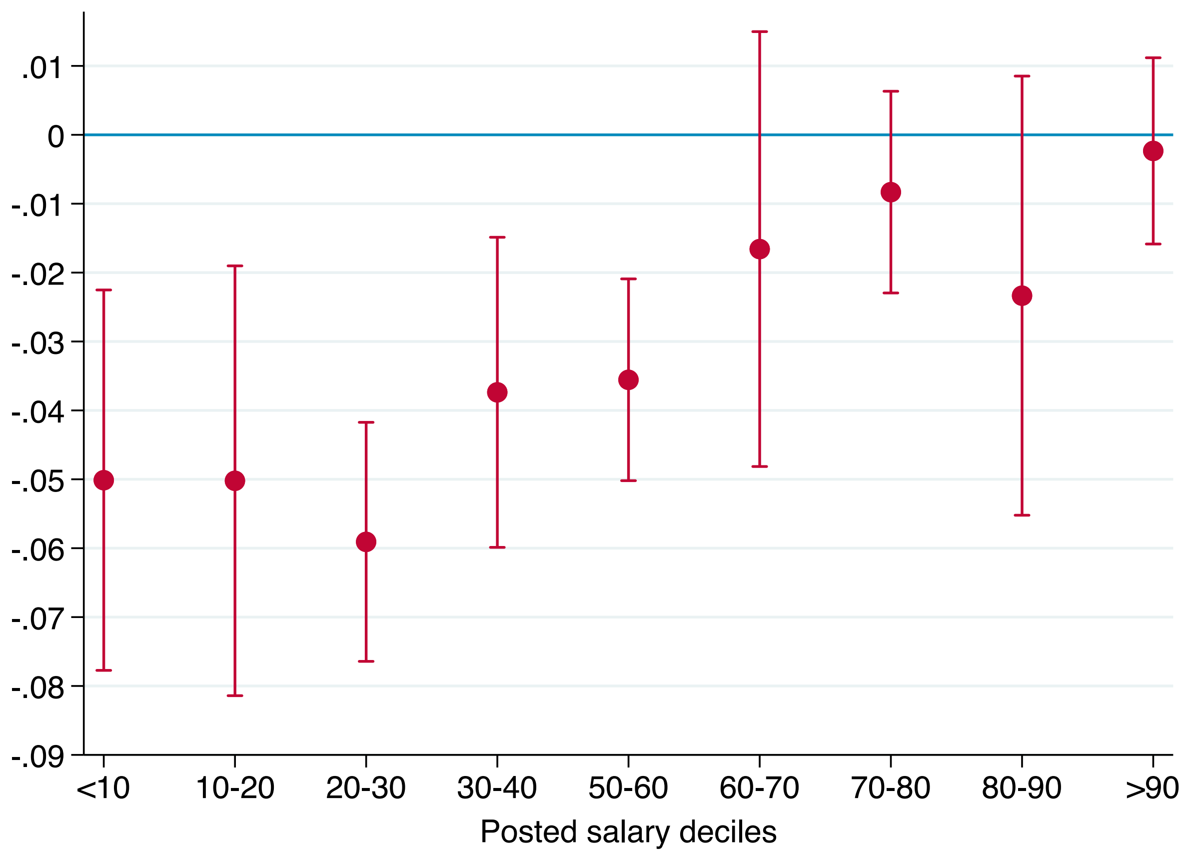
Notes: Author's calculations based on (1) degree awards in 2015 and 2016 from IPEDS; (2) administrative records on F-1 student visas in 2015 and 2016 from the US Immigration and Customs Enforcement (ICE); (3) administrative records on OPT in 2015 and 2016 from ICE; (4) administrative records on H-1B work visas in 2015 and 2016 from the US Citizenship and Immigration Services; (5) share of foreign master's degree students who received a bachelor's degree in the US from NSF Survey of College Graduates 2015. See Appendix B for more estimation details.

Figure A.3: Distribution of university world ranking by country



Notes: Author's calculations. The sample contains all US and Chinese institutions ranked in the top 1,000 by the 2018 US News Best Global Universities. The count of Chinese universities excludes those located in Hong Kong and Taiwan.

Figure A.4: US-China gap in callback rates by posted salary deciles



Notes: Each dot represents the regression estimate for the US-China difference in callback rates in a posted pay decile. The regression follows the same specification as column (3) of Table 3, including an indicator for US degree, name fixed effects, self-statement templates fixed effects, and vacancy fixed effects. Standard errors are clustered at vacancy level. The caps are 95 percent confidence intervals. The 40-50 decile is omitted from the graph since it has no observations.

Table A.1: Comparison of job characteristics in the experiment, the companion employer survey and external surveys

<table>
<tr><th>Job characteristics</th><th>Audit experiment</th><th>CCG survey</th><th>EIC survey</th><th>MOE report</th><th>Companion survey</th></tr>
<tr><td>Wage distribution (annualized in USD)</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Less than $11,100</td><td>32%</td><td>45%</td><td>42%</td><td></td><td>45%</td></tr>
<tr><td>$11,100 and $14,800</td><td>31%</td><td>23%</td><td rowspan="2">40%</td><td></td><td>22%</td></tr>
<tr><td>$14,800 and $18,500</td><td>15%</td><td>12%</td><td></td><td>20%</td></tr>
<tr><td>More than $18,500</td><td>22%</td><td>20%</td><td>18%</td><td></td><td>18%</td></tr>
<tr><td>Firm ownership</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Foreign owned</td><td>24%</td><td>27%</td><td>22%</td><td>29%</td><td>15%</td></tr>
<tr><td>Chinese owned</td><td>76%</td><td>73%</td><td>78%</td><td>71%</td><td>85%</td></tr>
<tr><td>Firm size</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Less than 500 employees</td><td>70%</td><td>63%</td><td></td><td></td><td>55%</td></tr>
<tr><td>More than 500 employees</td><td>30%</td><td>37%</td><td></td><td></td><td>45%</td></tr>
<tr><td>Occupation</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Accounting/finance/banking</td><td>36%</td><td>15%</td><td></td><td></td><td>12%</td></tr>
<tr><td>Sales/customer service/marketing</td><td>37%</td><td>17%</td><td></td><td></td><td>19%</td></tr>
<tr><td>Software/network/IT</td><td>26%</td><td>16%</td><td></td><td></td><td>21%</td></tr>
<tr><td>Other</td><td>0%</td><td>52%</td><td></td><td></td><td>48%</td></tr>
</table>

Notes: Empty fields mean data are not available. CCG survey refers to the “2017 Report on Employment and Entrepreneurship of Chinese Returnees” by the Center for China and Globalization and Zhaopin.com with a sample size of 1,821 valid responses. EIC survey refers the to “2019 Report on Employability of Chinese Returning Students Studied Abroad” by the EIC Education with a sample size of 11,570 valid responses. MOE report refers to the “’2015 The Blue Book for Chinese Returning Students’ Employment” by the Ministry of Education with a sample size of over 10,000. One caveat of all the external surveys is that they include jobs at all levels for returning students, not just limit to jobs for bachelor’s degrees.

Table A.2: Shares of enrollment and degrees awarded in the US by program

Degree programs	Chinese enrollment shares for 2014 cohort	Degrees awarded to all foreign students
Business related	0.318	0.310
Mathematics and statistics	0.108	0.046
Economics	0.105	0.073
Engineering	0.101	0.123
Computer sciences	0.088	0.064
Visual and performing arts	0.065	0.054
Sciences	0.055	0.059
Communication related	0.036	0.039
Psychology	0.026	0.034
Other social sciences	0.022	0.038
Other programs	0.077	0.159

Notes: Chinese enrollment shares are for students who entered in the fall of 2014 and data are from administrative records of individuals with F-1 student visas, which classify programs using Classification of Instructional Programs (CIP) codes. Data on bachelor's degrees awarded to all foreign students are from 2017 IPEDS, which also classifies programs using CIP codes. Data on degrees awarded to Chinese students are not available.

Table A.3: US institutions used in the experiment

Name	Selectivity group	Location
Boston College	very selective	US
Boston University	very selective	US
Brandeis University	very selective	US
Carnegie Mellon University	very selective	US
Case Western Reserve University	very selective	US
College of William and Mary	very selective	US
Columbia University	very selective	US
Cornell University	very selective	US
Duke University	very selective	US
Emory University	very selective	US
Georgia Institute of Technology	very selective	US
Lehigh University	very selective	US
New York University	very selective	US
Northeastern University	very selective	US
Northwestern University	very selective	US
Pennsylvania State University	very selective	US
Rensselaer Polytechnic Institute	very selective	US
Rice University	very selective	US
University of California Berkeley	very selective	US
University of California Davis	very selective	US
University of California Irvine	very selective	US
University of California Los Angeles	very selective	US
University of California San Diego	very selective	US
University of California Santa Barbara	very selective	US
University of Illinois Urbana-Champaign	very selective	US
University of Miami	very selective	US
University of Michigan Ann Arbor	very selective	US
University of North Carolina at Chapel Hill	very selective	US
University of Rochester	very selective	US
University of Southern California	very selective	US
University of Virginia	very selective	US
University of Wisconsin Madison	very selective	US
Wake Forest University	very selective	US
Washington University in St. Louis	very selective	US
Baylor University	selective	US
Drexel University	selective	US
Fordham University	selective	US
George Washington University	selective	US
Indiana University	selective	US
Marquette University	selective	US
Miami University	selective	US
Michigan State University	selective	US

Ohio State University	selective	US
Purdue University	selective	US
Rutgers University New Brunswick	selective	US
Saint Louis University	selective	US
Southern Methodist University	selective	US
SUNY Binghamton	selective	US
SUNY Buffalo	selective	US
SUNY Stony Brook	selective	US
Syracuse University	selective	US
University of California Santa Cruz	selective	US
University of Colorado Boulder	selective	US
University of Connecticut	selective	US
University of Delaware	selective	US
University of Denver	selective	US
University of Georgia	selective	US
University of Iowa	selective	US
University of Maryland	selective	US
University of Massachusetts Amherst	selective	US
University of Minnesota	selective	US
University of Pittsburgh	selective	US
University of Texas Austin	selective	US
University of Tulsa	selective	US
University of Vermont	selective	US
University of Washington	selective	US
Virginia Tech	selective	US
Worcester Polytechnic Institute	selective	US
Arizona State University	inclusive	US
California State University, Fullerton	inclusive	US
Colorado State University	inclusive	US
Depaul University	inclusive	US
Duquesne University	inclusive	US
Hofstra University	inclusive	US
Indiana University of Pennsylvania	inclusive	US
Iowa State University	inclusive	US
Kansas State University	inclusive	US
Kent State University	inclusive	US
Ohio University	inclusive	US
Oklahoma State University	inclusive	US
Oregon State University	inclusive	US
Pace University	inclusive	US
San Diego State University	inclusive	US
St. John’s University	inclusive	US
Suffolk University	inclusive	US
SUNY Albany	inclusive	US
Temple University	inclusive	US

University of Alabama	inclusive	US
University of Arizona	inclusive	US
University of California Riverside	inclusive	US
University of Cincinnati	inclusive	US
University of Colorado Denver	inclusive	US
University of Dayton	inclusive	US
University of Kansas	inclusive	US
University of Kentucky	inclusive	US
University of Massachusetts Boston	inclusive	US
University of Missouri Columbia	inclusive	US
University of Nebraska Lincoln	inclusive	US
University of New Hampshire	inclusive	US
University of North Carolina at Greensboro	inclusive	US
University of Oklahoma	inclusive	US
University of Oregon	inclusive	US
University of Pacific	inclusive	US
University of San Francisco	inclusive	US
University of South Florida	inclusive	US
University of Tennessee	inclusive	US
University of Toledo	inclusive	US
University of Utah	inclusive	US
University of Wisconsin Milwaukee	inclusive	US
Utah State University	inclusive	US
Washington State University	inclusive	US

Table A.4: Chinese institutions used in the experiment

Name	Selectivity group	Location
Beihang University	Very selective	Beijing
Beijing Institute of Technology	Very selective	Beijing
Beijing Normal University	Very selective	Beijing
China Agricultural University	Very selective	Beijing
Minzu University of China	Very selective	Beijing
Peking University	Very selective	Beijing
Renmin University of China	Very selective	Beijing
Tsinghua University	Very selective	Beijing
East China Normal University	Very selective	Shanghai
Fudan University	Very selective	Shanghai
Shanghai Jiao Tong University	Very selective	Shanghai
Tongji University	Very selective	Shanghai
Beijing Jiaotong University	Selective	Beijing
Beijing Forestry University	Selective	Beijing
Beijing University of Chemical Technology	Selective	Beijing
Beijing University of Posts and Telecom	Selective	Beijing
Beijing University of Technology	Selective	Beijing
Central University of Finance and Economics	Selective	Beijing
China University of Political Science and Law	Selective	Beijing
North China Electric Power University	Selective	Beijing
University of International Business and Economics	Selective	Beijing
University of Science and Technology Beijing	Selective	Beijing
Donghua University	Selective	Shanghai
East China University of Science and Technology	Selective	Shanghai
Shanghai University	Selective	Shanghai
Shanghai University of Finance and Economics	Selective	Shanghai
Beijing City University	Inclusive	Beijing
Beijing Information Science and Technology University	Inclusive	Beijing
Beijing Institute of Fashion Technology	Inclusive	Beijing
Beijing Institute of Graphic Communication	Inclusive	Beijing
Beijing Institute of Petrochemical Technology	Inclusive	Beijing
Beijing Language and Culture University	Inclusive	Beijing
Beijing Technology and Business University	Inclusive	Beijing
Beijing Union University	Inclusive	Beijing
Beijing University of Agriculture	Inclusive	Beijing
Beijing University of Civil Engineering and Architecture	Inclusive	Beijing
Beijing Wuzi University	Inclusive	Beijing
Canvard College, Beijing Tech. and Bus. Univ.	Inclusive	Beijing
Capital Normal University	Inclusive	Beijing
Capital University of Economics and Business	Inclusive	Beijing
Century College, Beijing Univ. of Posts and Telecom	Inclusive	Beijing
China University of Labor Relations	Inclusive	Beijing

Gengdan Institute of Beijing University of Technology	Inclusive	Beijing
North China University of Technology	Inclusive	Beijing
East China University of Political Science and Law	Inclusive	Shanghai
Sanda University	Inclusive	Shanghai
Shanghai Business School	Inclusive	Shanghai
Shanghai Dian Ji University	Inclusive	Shanghai
Shanghai Institute of Technology	Inclusive	Shanghai
Shanghai Jian Qiao University	Inclusive	Shanghai
Shanghai Lixin University of Accounting and Finance	Inclusive	Shanghai
Shanghai Maritime University	Inclusive	Shanghai
Shanghai Normal University	Inclusive	Shanghai
Shanghai Normal University Tianhua Collage	Inclusive	Shanghai
Shanghai Ocean University	Inclusive	Shanghai
Shanghai Second Polytechnic University	Inclusive	Shanghai
Shanghai University of Electric Power	Inclusive	Shanghai
Shanghai University of Engineering Science	Inclusive	Shanghai
Shanghai Univ. of International Bus. and Economics	Inclusive	Shanghai
Shanghai University of Political Science and Law	Inclusive	Shanghai
University of Shanghai for Science and Technology	Inclusive	Shanghai
Xianda College of Economics and Humanities	Inclusive	Shanghai

Table A.5: Interview regressions by occupation

	All (1)	All (2)	All (3)	Business (4)	CS (5)
US degree	-0.029^{***}	-0.029^{***}	-0.029^{***}	-0.031^{***}	-0.024^{***}
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)
Working full time		-0.018^{*}			
		(0.009)			
Female		0.028^{***}			
		(0.007)			
Spring job season		0.020^{***}			
		(0.007)			
China interview rate	0.153	0.153	0.153	0.178	0.083
Observations	26,036	26,036	26,036	19,108	6,928
F(labor markets)		0.000			
F(statement)		0.993	0.989	0.974	0.812
F(names)			0.559	0.360	0.435
Vacancy FE			Yes	Yes	Yes

Notes: The dependent variable is an indicator for receiving personalized interview offers from potential employers. Degrees from China is the omitted education category. Column 2 includes fixed effects for self-statement templates and labor markets, where each labor market is a city-occupation pair. Columns 3-5 include fixed effects for names and self-statement templates. p-values are reported for F-tests that these fixed effects are zero. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table A.6: Callback differences by institution group for all jobs

		Reference country: US		Reference country: China		
	Mean	Selective	Inclusive	V. selective	Selective	Inclusive
	(1)	(2)	(3)	(4)	(5)	(6)
Degree country: US						
Very selective	0.142	0.007	0.011^{**}	-0.031^{***}	-0.030^{***}	-0.011^{**}
		(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
		5.36%	**8.94%**	**-18.07%**	**-17.71%**	**-7.16%**
Selective	0.135	-	0.004	-0.038^{***}	-0.038^{***}	-0.018^{***}
			(0.005)	(0.006)	(0.006)	(0.006)
			3.27%	**-22.29%**	**-21.94%**	**-11.91%**
Inclusive	0.128	-	-	-0.043^{***}	-0.042^{***}	-0.022^{***}
				(0.006)	(0.005)	(0.005)
				-24.71%	**-24.37%**	**-14.65%**
Degree country: China						
Tier 1	0.172	-	-	-	0.001	0.020^{***}
					(0.006)	(0.006)
					0.44%	**13.26%**
Tier 2	0.172	-	-	-	-	0.019^{***}
						(0.006)
						12.76%
Tier 3	0.153	-	-	-	-	-

Notes: Column 1 reports mean callback rates. Each pair of nonidentical institution groups has three statistics. Regression coefficients and standard errors are from the specification in column 3 of Table 3, where the US degree indicator is replaced by five dummies for institution types, and the omitted category is the reference group of the corresponding column. The percentage difference is the ratio of the coefficient to the mean callback rate of the omitted education category. The estimation sample size is 26,036 in all cases. The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table A.7: Callback differences by institution group for business jobs

		Reference country: US		Reference country: China		
	Mean (1)	Selective (2)	Inclusive (3)	V. selective (4)	Selective (5)	Inclusive (6)
Degree country: US						
Very selective	0.166	0.007	0.013**	−0.029***	−0.034***	−0.013*
		(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
		4.03%	**8.81%**	**-14.78%**	**-17.00%**	**-7.16%**
Selective	0.162	-	0.007	−0.035***	−0.041***	−0.019***
			(0.006)	(0.007)	(0.007)	(0.007)
			4.53%	**-18.12%**	**-20.25%**	**-10.79%**
Inclusive	0.153	-	-	−0.042***	−0.048***	−0.026***
				(0.007)	(0.007)	(0.007)
				-21.65%	**-23.68%**	**-14.63%**
Degree country: China						
Tier 1	0.196	-	-	-	−0.005	0.016**
					(0.007)	(0.007)
					-2.61%	**8.93%**
Tier 2	0.201	-	-	-	-	0.021***
						(0.007)
						11.85%
Tier 3	0.180	-	-	-	-	-

Notes: Column 1 reports mean callback rates. Each pair of nonidentical institution groups has three statistics. Regression coefficients and standard errors are from the specification in column 4 of Table 3, where the US degree indicator is replaced by five dummies for institution types, and the omitted category is the reference group of the corresponding column. The percentage difference is the ratio of the coefficient to the mean callback rate of the omitted education category. The estimation sample size is 19,108 in all cases. The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table A.8: Callback differences by institution group for computer science jobs

		Reference country: US		Reference country: China		
	Mean	Selective	Inclusive	V. selective	Selective	Inclusive
	(1)	(2)	(3)	(4)	(5)	(6)
Degree country: US						
Very selective	0.074	0.010	0.007	-0.037^{***}	-0.019^{**}	-0.005
		(0.009)	(0.009)	(0.010)	(0.010)	(0.009)
		16.43%	**11.17%**	**-34.64%**	**-21.61%**	**-6.91%**
Selective	0.060	-	-0.003	-0.047^{***}	-0.029^{***}	-0.015^{*}
			(0.008)	(0.009)	(0.009)	(0.009)
			-4.98%	**-43.88%**	**-32.66%**	**-19.76%**
Inclusive	0.061	-	-	-0.044^{***}	-0.026^{***}	-0.012
				(0.009)	(0.009)	(0.009)
				-41.03%	**-29.25%**	**-15.80%**
Degree country: China						
Tier 1	0.107	-	-	-	0.018^{*}	0.032^{***}
					(0.010)	(0.010)
					19.83%	**41.30%**
Tier 2	0.090	-	-	-	-	0.014
						(0.009)
						18.23%
Tier 3	0.077	-	-	-	-	-

Notes: Column 1 reports mean callback rates. Each pair of nonidentical institution groups has three statistics. Regression coefficients and standard errors are from the specification in column 5 of Table 3, where the US degree indicator is replaced by five dummies for institution types, and the omitted category is the reference group of the corresponding column. The percentage difference is the ratio of the coefficient to the mean callback rate of the omitted education category. The estimation sample size is 6,928 in all cases. The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table A.9: Callback regressions by posted salary quartiles (alternative measure)

	All (1)	Below 25th percentile (2)	25th-50th percentile (3)	50th-75th percentile (4)	Above 75th percentile (5)
US degree	-0.068^{***}	-0.051^{***}	-0.051^{***}	-0.029^{***}	-0.005
	(0.007)	(0.009)	(0.007)	(0.007)	(0.005)
× salary (in $1,000s)	0.003^{***}				
	(0.000)				
China callback rate	0.165	0.211	0.219	0.160	0.107
Observations	26,036	3,480	6,980	7,196	8,380
US degree diff wrt (2)			0.001	0.023^{**}	0.047^{***}
			(0.012)	(0.011)	(0.011)
Vacancy FE	Yes	Yes	Yes	Yes	Yes

Notes: Salaries are proxied by the lower bound of the posted salary. The median salary is 72,000 RMB or $11,096. The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Degrees from China is the omitted education category. All columns include fixed effects for names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table A.10: Callback regressions by the number of job applicants quartiles

	All (1)	Below 25th percentile (2)	25th-50th percentile (3)	50th-75th percentile (4)	Above 75th percentile (5)
US degree	-0.033^{***}	-0.032^{***}	-0.039^{***}	-0.034^{***}	-0.020^{***}
	(0.004)	(0.007)	(0.007)	(0.007)	(0.005)
$\times$ 100 applicants	0.001^{**}				
	(0.001)				
China callback rate	0.165	0.233	0.196	0.150	0.088
Observations	25,817	6,193	6,645	6,482	6,716
US degree diff wrt (2)			−0.007	−0.002	0.012
			(0.010)	(0.010)	(0.009)
Vacancy FE	Yes	Yes	Yes	Yes	Yes

Notes: The number of job applicants for each posting is collected at 1 month after a posting is created through paid service of the job site. The 25th percentile of job applicants number is 31, the median job applicants number is 61, and the 75th percentile of job applicants number is 140. The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Degrees from China is the omitted education category. All columns include fixed effects for names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table A.11: Callback regressions by firm ownership and Chinese work experience

	CN work exp		No CN work exp	
	Chinese (1)	Foreign (2)	Chinese (3)	Foreign (4)
US degree	-0.032^{***}	-0.017^{**}	-0.041^{***}	-0.022^{*}
	(0.005)	(0.008)	(0.007)	(0.013)
China callback rate	0.167	0.162	0.161	0.176
Observations	14,348	4,396	5,592	1,700
US degree diff wrt the first col within group		0.015		0.018
		(0.009)		(0.015)
Vacancy FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is an indicator for receiving personalized positive contacts from potential employers. Foreign-owned firms include firms owned by regions outside of China and joint ventures. Degrees from China is the omitted education category. All columns include fixed effects for names and self-statement templates. Standard errors are clustered at the vacancy level. *** = significant at 1 percent level, ** = significant at 5 percent level, * = signficant at 10 percent level.

Table A.12: The most important reason for hiring managers choosing a US university over a Chinese university in the employer survey

	Share chosen
Candidates educated in China have better outside options	**0.248**
"Students from the unselected school are overqualified for the job"	0.158
"Students from the unselected school are more likely to take other jobs"	0.056
"Students from the unselected school are more likely to quit"	0.033
Negative selection of who studies at the Chinese institution	**0.125**
"Students admitted to the selected school are better"	
Negative selection of who applies from the Chinese institution	**0.069**
"Students from the unselected school applying for the job are worse than the average at their school"	
US schools have better employer network	**0.030**
"The selected school has a strong connection with the company"	
Students from US schools fit firm culture more	**0.092**
"Students from the selected school are more likely to suit the company's work culture"	
US schools provide better education	**0.168**
"The selected school provides a better college education"	
Students from US schools have better English	**0.215**
"Students from the selected school have better English skill needed for the job"	
Others	**0.053**
"If other, please specify"	

Notes: The employer survey asks hiring managers to choose between two other-wise candidates except their undergraduate institutions to offer an interview. Each hiring managers is asked to make this decision three times for three different set of schools. Among 1,521 decisions made by 507 hiring managers, 80.28 percent offered candidates educated in China an interview instead of candidates educated in the US. While 94.87 percent of hiring managers offered an interview to Chinese-educated candidates at least once, 40.43 percent offered US-educated candidates at least once. Following each question on whom to offer an interview, hiring managers are asked to select the most important reason for making the interview decision. Ten reasons are listed and respondents can enter their own texts. The quoted texts in the table are what shown to the employers and the texts in bold indicate the targeted mechanisms of the quoted texts.

B Non-Experimental Data Appendix

B.1 Estimates of transition probabilities

In this section, I first describe how I estimate transition probabilities in A.2 using data from various sources. I calculate the probabilities for the 2015 and 2016 cohorts together to smooth potential seasonal variation while capturing the most recent cohorts that have data available. I then describe briefly how I obtain an estimate for the share of college graduates in China who go to graduate school.

Step 1: Using IPEDS, I obtain the number of bachelor's degrees awarded to all international students in 2015 and 2016. To my best knowledge, reliable data on student completion in the US by nationality have not been made available. Given that Chinese students have higher average SAT scores than other international students and SAT scores are correlated with graduation rates, it is reasonable to use Chinese enrollment share to approximate the share of degrees awarded to Chinese students in the US I compute the Chinese enrollment share among all international undergraduate (UG) students in the US using administrative records on F-1 student visas obtained via a Freedom of Information Act (FOIA) request to the US. Immigration and Customs Enforcement (ICE). I sum Chinese students who started a bachelor's program in fall of 2015 and fall of 2016 and divide by that for all international students. I obtain a share estimate of 35 percent.

Step 2: I obtain the number of undergraduate students (for both total and Chinese) on the Optional Practical Training (OPT) programs in 2015 and 2016, using the administrative records obtained from a different FOIA request to ICE. These numbers and the numbers from Step 1 derive the share of foreign/Chinese students who stayed in the US via OPT after graduation. As shown in Appendix Figure A.2, the share is 30 percent for all international students and 24 percent for Chinese students. Note that OPT does not imply official employment in the US. During the 12 months of regular OPT, both self-employment and volunteering can maintain students' legal status, as long as the experience is directly related to their academic field. Students on OPT can leave the US at any time. They have obtained their diploma, although they are still classified as students. For STEM majors who qualify for a 24-month OPT extension, they must be formally employed in the US. Before May 2016, the STEM OPT extension was 16 months.

Step 3: I obtain the number of H-1B work visa approvals (for both total and Chinese) in 2015 and 2016 for those whose previous immigration status is F-1 student, using administrative records obtained via FOIA request from ICE. These numbers therefore capture students who were previously on OPT and obtained temporary work visas, which last three years with one time renewal. Employers in the US must be willing to sponsor an H-1B for a foreign national, and there is some filing cost usually around several hundred dollars. Work visa slots are capped at 65,000 per year since 2004 (20,000 extra slots for a master is or above), although they are not capped for nonprofit research organizations. In 2017, 236,000 petitions were received, and applicants participated in a lottery. Since students on STEM OPT can participate in the lottery more than one time, I multiply the number of H-1B approvals by 1.5 and use it to estimate the number of students who stay in the US to work beyond OPT. Combining numbers from Step 2, the share of OPT students who stayed via an H-1B visa is estimated to be 30 percent for all international students and 32 percent for Chinese students.

Step 4: To estimate the share of UG graduates who continue to graduate school in the US right after graduation, I first obtain the number of students (for both total and Chinese) who started a master's degree program or a doctoral program in fall 2015 and fall 2016, using administrative data on F-1 student visas from ICE. I then use the NSF Survey of College Graduates 2015 to estimate the share of foreign graduate students who received their bachelor's degrees in the US. I limit the sample to foreign students who are working on a master's/doctoral degree but received a bachelor's degree between 2011 and 2013. The share of foreign master's students who received their bachelor's in the US is 17 percent, and the share of foreign PhD students who received their bachelor's in the US is 7 percent. The survey sample is too small to compute these shares separately for Chinese students. Hence I use these shares for both all international students and Chinese students. Combining these shares with the number of newly enrolled master's/doctoral students and the number of bachelor's degrees awarded (from Step 1), about 25 percent of international UG go to graduate schools in the US right after graduation, and the number is 24 percent for Chinese students.

Step 5: Taking estimates together from Step 2 to Step 4, the share of international UG who leave the US is 1 minus the share on OPT and the share going to graduate school. Hence, 45 percent of international UG or 52 percent of Chinese UG leave the US right away (presumably to work overseas) upon graduation. Assuming that students on OPT who do not get work visas also leave the US, 66 percent of international UG or 69 percent of Chinese UG leave the US within a few years of graduation. Among students who participate in the labor market after graduation (i.e., not going to graduate school), 88 percent of international students or 90 percent of Chinese students leave the US within a few years.

Share of college graduates in China going to graduate school: First, I obtain the number of graduates from bachelor's-degree-granting institutions (N), the number of entrants to master's programs (M_1), and the number of entrants to doctoral programs (M_2) in China for year 2016 from the China Statistical Yearbook (NBSC, 2017). Given that many students complete a master's before doing a PhD, I adjust the number of doctoral entrants straight from UG by multiplying 0.5. The number of doctoral entrants is small in China, and it does not influence the final estimate by too much.

Second, I obtain the number of Chinese master's students (F_1) and the number of Chinese doctoral students (F_2) who started in fall 2016 in the US using administrative data from ICE. Third, since it is too costly to collect data for all Chinese students working on a graduate degree outside of China, I estimate the ratio of Chinese graduate students in the US to Chinese graduate students in five popular destinations (r_f): US, UK, Australia, Canada, and Japan. This ratio underestimates the number Chinese college graduates working on a graduate degree abroad, and thus provides conservative estimates for my purpose.

I obtain data on Chinese graduate enrollment in 2016 in these five countries from the following sources: International Institute of Education (US); Higher Education Statistics Agency (UK); Department of Education and Training (Australia); Immigration, Refugees and Citizenship (Canada); and Japan Student Services Organization. The numbers are not available separately by academic level for Japan and Canada, so I multiply their total Chinese enrollment in higher education by 0.5. Note that Chinese UG enrollment in these two countries is likely lower than graduate enrollment, so this approximation is conservative. From these data, I compute r_f, which is 0.43—the share of Chinese graduate students in the US among all Chinese graduate students in the five countries.

Finally, taking the shares of master's and doctoral students who did not receive their bachelor's degree in the US (see Step 4 above), I estimate the share of college graduates in China going to graduate school as:

$$\frac{M_1 + 0.5M_2 + 0.83F_1/r_f + 0.93 * 0.5F_2/r_f}{N}$$

which gives an estimated share of 19 percent. This rough conservative estimate is similar to the share of Chinese college graduates in the US who go to graduate school: 24 percent.

B.2 Percentiles of average test scores for enrolled students

In this section, I describe how I compile data on test score percentiles at sample institutions used for Figure 3. First, I obtain test score data for the entering class in fall 2017 at sample US institutions from the US News' Academic Insights (AI) database. For each school, AI reports the 25th percentile and the 75th percentile for the SAT and ACT scores. I first take the average of these two percentiles for the SAT and ACT and then map them to the percentile distribution in the year of 2016. This assumes that most students entering the class of 2017 took the exams in 2016. The percentile distribution for both exams is very stable over time, so this assumption has little impact.

I then take the average of SAT percentile and ACT percentile for each school, which is the final percentile of the average test score used for Figure 3. Note that the AI database also reports the average SAT and ACT score for a large portion of my sample institutions. Using that average instead of averaging the two quartiles yield very similar results. Since I do not observe the average test score for all sample schools, I choose to average out the two quartiles.

Second, I obtain test score data for the entering class in fall 2017 at sample Chinese institutions from the official college admission website referenced by China's Ministry of Education: gaokao.chsi.com.cn. I look up the data on test scores for each individual school. The website provides the average test scores for students newly enrolled by cohort for students from different regions. Not all Chinese regions take the same national college entrance exam, and schools have quotas for each region. Both Beijing and Shanghai administer their own college entrance exam for local high school students. Hence, for schools in Beijing, I collect test scores for students from Beijing. For schools in Shanghai, I collect test scores for students from Shanghai.

The college admissions system in China is further complicated by a science track and an art track. Students choose one track in high school and take somewhat different versions of the entrance exam. While Beijing still had this tradition for the year 2017, all students in Shanghai took the same exam. Hence, for schools in Beijing, I collect the average test score for both tracks. I map these test scores to the percentile distribution in 2017—students from the same college cohort have to take the exam in the same year, and the exam happens right before they graduate from high school. The percentile distribution is published online, although both are only available for the most recent years. For schools in Beijing, I then average percentiles for the science track and the art track. Together with the percentiles for schools in Shanghai, these are the average test scores used for Figure 3.

Comparison of US and Chinese institutions based on this test score measure should be approached with caution. Exams used in the two countries are quite different and carry different weights in college admissions. One reasonable way to think about the comparison is to assume that students from both countries have similar ability distribution, and these exams are effective in measuring the percentiles of the distribution.

C Additional Details on Experiment Implementation

C.1 Resume construction

Names: I use the most common last names in China and select first names from the 10 most commonly used first names for babies born in the 1990s. By combining these names, I create four generic names for female applicants and four for male applicants. Note that all of the eight names signal gender, as most Chinese names do, although the online job board used in the experiment requires the applicant's gender.

Hometown and college location: If I vary hometown and the location of Chinese colleges, there are several immediate concerns of selection that employers may infer from those attributes. Unlike in the US, where job seekers work and live anywhere of their choice, labor mobility in China is impacted by a household registration system called hukou in Chinese (Song 2014). There is a lot of evidence that employers have differential preferences and, in some cases, restrictions in hiring employees without a local hukou. Hukou in Beijing and Shanghai are particularly difficult to obtain, providing benefits such as housing purchases and public education for children. Hence, I kept the hometown (required as a resume entry by the job board) to be the same as the job market to shut down employer concerns on hukou. Once the hometown city is fixed, signaling a college located outside the Beijing and Shanghai raises concerns about selecting who leaves the city for college and who comes back among the Chinese educated candidates. It is particularly relevant to people who live in Beijing and Shanghai as they are the largest cities in China, and their residents are most likely to stay in the city if possible. Although my field experiment is already on the larger end of existing audit studies, I had to shut down these channels to focus on other tests of potential mechanisms.

Once the hometown city is fixed, signaling a college location outside the Beijing and Shanghai raises concerns about selection on who leaves the city for college and who comes back among the Chinese educated candidates. It is particularly relevant to people who live in Beijing and Shanghai as they are the largest cities in China and their citizens are most likely to stay in the city if possible.

Employer name and work experience: Each work experience listed on the resume consists of 4 parts: (1) job title, (2) employment time, (3) employer name, and (4) bullet points that describe tasks performed. In reviewing thousands of actual resumes from job seekers in the same set of institutions, my research assistants and I find that for entry-level jobs, the description of job tasks performed are highly similar between firms in the US and China.

For example, all accounting experience would mention working on balance sheet data. Hence, we ensured (1), (2), and (4) are the same in expectation between US-educated and Chinese-educated candidates. That is, we randomly assign the same data bank for (1), (2), and (4) to all candidates while making sure they are different when applying for the same job.

As for employer name (3), I picked "the average employer name" from both countries. That is, I picked employer names that are either unheard of or are common to see but not getting too much attention from hiring managers. Based on my conversation with over a handful of experienced hiring managers, only several stellar employer names make resume screeners pay particular attention. Otherwise, screeners mainly focus on task descriptions (4).

High school: I choose local elite (exam) high schools from high school rank based on the college entrance rate. I select four elite schools in Beijing and four elite schools in Shanghai, where nearly all graduates enrolled in a bachelor's-degree-granting institution in recent years. Both Beijing and Shanghai have two elite high schools that are much more prestigious than others. I exclude these schools to avoid the concern that their students are not likely to attend an inclusive institution in either country. High schools are listed right below the college institution.

Test score: I first collect data on the average test score for newly enrolled students in sample Chinese degree programs. I compute the median of the average score within each selectivity group. I use two test scores on resumes for applicants from US institutions. The first score equals to the median of the very selective group, and the second score equals to the median of the selective group. I do not signal a median from the inclusive group, because it might be strange to signal a test score that is not very high. For applicants from very selective and selective US institutions, I randomize between these two scores. For applicants from inclusive US institutions, I only use the second score. When signaling these scores, they are listed right below the college institution but above the elite high school, if both are signaled. Right next to the test score, a short note indicates the score is high enough to get into a very selective/selective school in the year of high school graduation.

Self-statement templates: The resume template on the job board requires a short description of the applicant. Based on the bank of real resumes, these descriptions have a few common patterns; they usually mention identities such as having a suitable personality and good work ethic. I create several generic templates for each occupation and experience-level group. I control template fixed effects in the preferred specification, and they do not predict callbacks. This is consistent with my conversations with hiring managers in China, who say that they rarely look at the self-statement.

Other skills: For business jobs, all applicants list Microsoft Word, Excel, and PowerPoint as their software skills. For computer science jobs, all applicants list some popular programing language skills. All Chinese applicants also indicate that they have passed the two English exams required at most colleges in China (CET-4 and CET-6).

C.2 Implementation

Applying for a job: A large number of research assistants (RAs) are divided into small groups of two or three. Each group is assigned a specific labor market. They search for qualified target jobs based on the targeted city, occupation, degree requirement, experience level, and posted time. They select jobs with a few additional filters: (1) jobs with posted salary below the minimum requirement (3,000 RMB, or about $460 a month), which is the 5^{th} percentile for all jobs requiring a bachelor's degree; (2) jobs with inappropriate use of language and that include an unrealistic income in the job title; (3) intermediate companies that perform indirect hiring for other firms. RAs also check whether a job has already been applied for and record newly targeted jobs on a commonly accessible worksheet. Once a new target job is identified, RAs start to fill out the first job application. The four applications sent to the same job are sent within two to three days, with at least a four-hour gap in between. The send order is randomized. RAs collect job posting information using a web-scraping program.

Recording outcomes: Employers' responses are tracked via phone, text messages, and emails. RAs follow a standard protocol to answer each phone call. After recording an employer's firm name and purpose, RAs say that they greatly appreciate the employer's interest and politely tell the employer that they have just taken another offer. When recoding the purpose, RAs distinguish between an invitation to a interview or other reasons. For applications submitted near the end of the experiment, I give employers almost a month to respond. In practice, most employers respond within the first three weeks. A few employers also respond on the online job board's system, and RAs also check that. Two and half to three and half weeks after an application is submitted, RAs log back into the account and collect information on the number and composition of other job applicants (a paid service) using a web-scraping program.

Quality checks: The amount of work for each RA is massive: Each must fill out hundreds of job applications. In contrast to typical audit studies in the US, where an RA simply uploads a pre-generated resume, filling out a new application every time is very time consuming. In addition, due to a limitation in the design of the online job board, each RA manages about 100 email accounts and 16 phone numbers. Taking phone calls also requires more work than audit studies in the US, which rely on transcribing voicemails. No voicemail service exists in China.

To undertake the experiment with many new practical challenges on a large-scale, I develop several ways to optimize work efficiencies for a large team of RAs and ensure data quality. This includes, but is not limited, to identifying responsible and productive RAs, developing an easy-to-understand training protocol, and developing a smooth procedure for searching for jobs, filling out applications, communicating with other team members, collecting posting information, and tracking responses.

In addition to these efforts, I also developed strict quality-control check procedures. First, to ensure that applications are filled out correctly, I choose several lead RAs to be in charge of checking the work done by members in other labor markets. The lead RAs randomly check a few job applications for each member twice a week, with more frequent checks in the beginning of the experiment and for RAs who have made mistakes. In addition, each RA also randomly selects a few job applications to check themselves, and sometimes I also ask them to check their peers' work. Lastly, RAs record key randomized resume characteristics on a local sheet every time they submit a job. I cross-check this information with the actual resume data.

Second, to monitor the quality of response recording, every RA is required to update new responses received and report phone call statistics on a daily basis. I monitor these statistics daily. Note that all phone records are provided by the phone company. If RAs miss a call, they call that number back as soon as possible during business hours, and continue to call that number for three days. If all fail to reach the employer, they wait a week for the employer to call back again. RAs make another call at the end of that week before stopping trying to call back. In practice, many employers call multiple times if RAs miss a call and RAs are able to call most of the employers back. In a few instances in which numbers are not identified, I look them up on Baidu, and all have been reported as either "advertisement calls" or "fraud calls."

D Employer Survey in English

First Page of the Survey

Dear hiring managers:

We would like to invite you to contribute to our survey on understanding how different colleges are perceived in Chinese labor markets. To participate, you need to have experience in selecting job applicants at your firm for entry-level jobs. Entry-level jobs are for current college seniors or college graduates within 2 years. Your information will be kept strictly confidential and only be used for academic research.

This survey takes on average about 5 minutes to complete. Please read the questions very carefully and answer honestly. If you don't know an answer, just give US your best guess. It would help the integrity of our research if you complete the entire survey.

If you return the picture of the survey's completion page, you will receive a small nice gift and enroll in five lottery draws of 1,000 RMB each.

Note: Your participation in this study is purely voluntary. If you have any question about this study, you may contact US at laboreconresearch@gmail.com. If you have questions about the ethics about this study, please contact the ethics Board that approved the study at irb@princeton.edu.

Yes, I would like to take part in this study and confirm that I have experience in selecting job applicants at my firm for entry-level jobs requiring a bachelor's degree

Part 1: Basic Information

1. What is the name of the firm that you work for?

2. What is the most recent city where your firm has hired entry-level jobs requiring a Bachelor's degree?
   a. Beijing
   b. Shanghai
   c. Other (please specify)
   <Answer to this question decides the set of Chinese schools appearing in Part 2.>

3. In the past 12 months, has your company had any openings for entry-level jobs requiring a Bachelor's education?
   a. Yes
   b. No

<If b is chosen, prompts "Sorry, you are not qualified to participate in this survey. Your firm needs to have tried to hire an entry-level position requiring a bachelor's degree in the last 12 months" and skips to the end of the survey.>

4. Select one or more from below describing your responsibilities in the hiring process:
   a. Screen initial job applications/resumes
   b. Decide or jointly decide whom to offer interviews
   c. Interview job candidates
   d. Decide or jointly decide whom to receive job offers
   e. Decide or jointly decide wage and benefits offered
   f. None of the above
   <If f is chosen, prompts "Sorry, you are not qualified to participate in this survey. Please ask someone with experience in selecting job applicants for entry level jobs at your firm to participate" and skips to the end of the survey.>

5. What is your gender?
   a. Female
   b. Male

6. What is the year of your birth?
   <Dropdown bar from 1950 to 2000>

7. Please select your education status:
   a. Less than a 4-year college education
   b. 4-year Bachelor's degree
   c. Master's degree
   d. PhD

   <If b, c, or d are chosen in 7, show 8.>

8. Please select all types of post-secondary education experience you have had:
   a. 985 <China very selective>
   b. 211, not 985 <China selective>
   c. Not 211 and not 985 <China inclusive>
   d. US Top 50 <US very selective>
   e. US Top 51-100 <US selective>
   f. US Top 101-250 <US inclusive>
   g. Other foreign countries

9. In the last two years, has your firm hired a worker with a postsecondary degree from the US?
   a. Yes
   b. No

<I choose 2 schools (1 public and 1 private) with the largest Chinese student enrollment from each selectivity group. No school is too close to the ranking threshold of its selectivity group. The order of displayed is randomized.>

10. To the best of your knowledge, how are schools below ranked academically in the US for its undergraduate education?

	Top 1-50	Top 51-100	Top 101-250	Heard of but not sure	Never heard of
UC San Diego					
Michigan State Univ.					
Arizona State Univ.					
Boston Univ.					
Syracuse Univ.					
Temple Univ.					

<I choose 2 schools with the largest enrollment from each selectivity group. Based on firm's answer to question 2, local schools in Beijing or Shanghai are displayed. If in other cities, a mix of Beijing and Shanghai schools are displayed. The order of displayed is randomized.>

11. To the best of your knowledge, which category are schools below belong to in China?

<If a is chosen in 2, display:>	985	211 but not 985	Non 985 and 211	Heard of but not sure	Never heard of
Renmin Univ. of China					
Central Univ. of Fin. & Econ.					
Capital Univ. of Econ. & Bus.					
Beijing Inst. of Tech.					
Univ. of Intl. Bus. & Econ.					
Beijing City Univ.					

<If b is chosen in 2, display: Tongji Univ., East China Normal Univ., Shanghai Univ. of Fin. & Econ., Shanghai Univ., Shanghai Lixin Univ. of Acct. & Fin., Shanghai Univ. of Intl.

Bus. & Econ. If c is chosen in 2, display: Tongji Univ., Shanghai Univ. of Fin. & Econ., Shanghai Univ. of Intl. Bus. & Econ., Renmin Univ. of China, Central Univ. of Fin. & Econ., Beijing City Univ.>

12. Approximately how many people does your company employ?
    a. 1-50
    b. 50-150
    c. 150-500
    d. 500-1000
    e. 1000-5000
    f. 5000-10000
    g. More than 10000

13. What industry best describes your firm?
    a. IT/communication
    b. Accounting/finance/banking/insurance
    c. Manufacture/trade
    d. Pharmaceutical/medicine
    e. Advertising/media
    f. Real estate/architecture
    g. Education/professional services
    h. Services
    i. Transportation/logistics
    j. Energy/raw materials
    k. Government/non-profit

14. What is the ownership structure of your firm?
    a. Private
    b. Foreign owned (US)
    c. Foreign owned (Europe)
    d. Foreign owned (non-US and non-Europe)
    e. Joint venture (with US)
    f. Joint venture (with non-US)
    g. Government owned

15. How long have you been involved in hiring process in your career?
    a. Less than a year
    b. 1-3 years
    c. 4-6 years
    d. More than 6 years

16. Select one or more from below describing methods your company takes to look for job candidates for entry-level positions:
    a. 51job.com
    b. Zhaopin.com
    c. Boss Zhipin
    d. Other internet-based platforms
    e. Career fairs
    f. Other methods

17. Please select the occupation for which you have the most experience in hiring:
    a. Sales/customer service/marketing
    b. Accounting/finance/banking
    c. Computer science/IT
    d. Engineering
    e. Biology/medicine science
    f. Media/arts and design
    g. Human resource/administrative support
    h. Education
    i. Other (please specify)
    <If a or b is chosen, use business program weights in Part 2; If c is chosen, use computer science program weights in Part 2; If other options are chosen, use total Chinese enrollment as weights.>

18. What is the typical starting monthly pay at your firm for an entry-level job in <occupation answer from 17> that requires a Bachelor's degree?
    <Dropdown bar from below 2,000 RMB to above 20,000 RMB>

19. In your opinion, what is the monthly income for a worker with a Bachelor's degree from the US on an entry-level job in <occupation answer from 17> in <city answer

from 2>?
<Dropdown bar from below 2,000 RMB to above 20,000 RMB>

Part 2: Choice experiments with vignettes

Imagine your firm is hiring for an entry-level job in <occupation answer from 17> that requires a Bachelor's degree. There are two candidates with undergraduate education in relevant major, having resumes that are similar in every respect (e.g. major, gender, Hukou, description of work experience, software skills etc.), except they are attending or have graduated from different schools.

<Randomly select one comparison for the following question without replacement from 9 possible cases: China very selective (VS) vs. US VS, China VS vs. US selective, China VS vs. US inclusive, China selective vs. US VS, China selective vs. US selective, China selective vs. US inclusive, China inclusive vs. US VS, China inclusive vs. US selective, China inclusive vs. US inclusive. The question below illustrates an example of China VS vs. US VS>

20. The two schools are listed below. If you had to pick one candidate to offer an interview, which one would you choose? *<The order of school (country) displayed is randomized.>*
    a. *<Randomly drawn from China VS>* Beijing Normal University
    b. *<Randomly drawn from US VS>* University of California – Davis

21. Please select the most important reason from below that led you to make this choice and identify all other reasons. Otherwise, select "Not a reason":

	The most important reason (select only one)	Other reasons	Not a Reason
a. Students from the unselected school are overqualified for the job			
b. Students from the unselected school are more likely to take other jobs			
c. Students from the unselected school are more likely to quit			
d. Students from the unselected school applying for the job are worse than the avg. at their school			
e. The selected school provides a better college education			
f. Students admitted to the selected school are better			
g. The selected school has a strong connection with the company			
h. Students from the selected school are more likely to suit the company's work culture			
i. Students from the selected school have better English skill needed for the job			
j. If other, please specify			

22. In the scale of 1 to 5, please rate your knowledge about the undergraduate education quality for the two schools listed above: *<1. Don't know anything; 5. Very knowledgeable>*

    a. *<Same as in 20>* Beijing Normal University

    b. *<Same as in 20>* University of California – Davis

    <Repeat 20-22 two additional times with page transition making it clear that there are three different sets. The vignette is displayed every time.>

Part 3: Additional Mechanism Questions

The **entry-level jobs** mentioned below refer to jobs in <occupation answer from 17>, requiring a bachelor's degree.

30. Overall, how much do you agree with the following statements about students with a US college degree and are looking for entry-level jobs in China? *<Likert 3 scale: disagree, neutral, agree.>*
    a. They have low ability and cannot find a job in the US
    b. They value social environment (e.g. family, culture) in China
    c. They value job opportunities in China
    d. It is hard to work in the US because of visa challenge

31. Overall, how does family wealth status affect your decision about whom to offer an interview, for an entry-level job?
    a. I value applicants from wealthier families more
    b. I value applicants from wealthier families less
    c. I do not make this decision based on family wealth status

32. To the best of your knowledge, which type of candidates with a bachelor's education perform better during entry-level job interviews?
    a. Candidates educated in the US perform better
    b. Candidates educated in China perform better
    c. About the same
    d. I don't know

    <If a is chosen in 9, display 33 and 34.>

33. To the best of your knowledge, how does your company pay for entry-level jobs:
    a. Pay more to workers with degrees from the US
    b. Pay more to workers with degrees from China
    c. Pay everyone the same
    d. I don't know

34. To the best of your knowledge, on average, how would you compare the performance of workers after 1 year of working in an entry-level job?
    a. Workers with degrees from the US are better

b. Workers with degrees from China are better

c. About the same

d. I don't know

Part 4: Ending

- Would like to participate in the lottery for a 1,000 RMB prize?

  a. Yes

  b. No

  <If a is chosen above, show below.>

- Please enter your Wechat account and cell number in order to participate in the lottery. If you win a prize, your payment will be sent to your Wechat account within one month.