

Signals, Information, and the Value of College Names

Alex Eble and Feng Hu*

September 2022

Abstract

Colleges can send signals about their quality by adopting new, more alluring names. We study how this affects college choice and labor market performance of college graduates. Administrative data show name-changing colleges enroll higher-aptitude students, with larger effects for alluring-but-misleading name changes and among students with less information. A large resume audit study suggests a small premium for new college names in most jobs, and a significant penalty in lower-status jobs. We characterize student and employer beliefs using web-scraped text, surveys, and other data. Our study shows signals designed to change beliefs can have real, lasting impacts on market outcomes.

*Eble (corresponding author): Teachers College, Columbia University; eble@tc.columbia.edu. Hu: University of Science and Technology Beijing; feng3hu@gmail.com. Eble and Hu are co-first authors and contributed equally to all stages of the research. Order of authorship is alphabetical by author surname. We are grateful for generous input from many sources: the co-editor, Brian Jacob, and two anonymous referees, as well as Liz Ananat, Sandy Black, Beezer Cheble, Mingyu Chen, Sarah Cohodes, Jennifer Eggerling-Boeck, Haoran He, Prashant Loyalka, Jordan Matsudaira, Josh Merfeld, Randy Reback, Jonah Rockoff, Judy Scott-Clayton, Miguel Urquiola, Felipe Valencia, Chunbing Xing, and audience members at AEFPP, the China Econ Lab, the Columbia Committee on the Economics of Education, IFPRI, the NBER Education Program Fall Meetings, NEUDC, and the University of Minnesota. This project would not be possible without the tireless work of our research managers, Yanrong Liu, Xuecun Zhao, and, particularly, Yingli Lin. Cong An, Xinyu Feng, Xuejing Hao, Zhu Li, Qian Liu, Jing Lv, Xinru Lv, Lei Pan, Hongfeng Wang, and Yuanyaun Xu all provided research assistance. Eble acknowledges support from the National Academy of Education (NAEd) and the NAEd/Spencer Postdoctoral Fellowship Program. Hu acknowledges support from the Humanities and Social Science Fund of Ministry of Education of China (grant no. 19YJA790029).

1 Introduction

The information people possess affects the choices they make and the outcomes of market transactions (Akerlof, 1970; Tversky and Kahneman, 1974; Loewenstein et al., 2003). Starting with Spence (1973), imperfect information has been a powerful tool in the economic analysis of education (cf. Stiglitz 1975; Altonji 1993; Weiss 1995; Arcidiacono et al. 2010). Recent work has shown that providing better or more information to participants in educational markets can improve individual and market outcomes (Jensen, 2010; Hoxby and Turner, 2013; Andrabi et al., 2017; Dizon-Ross, 2019; Bergman, 2021). In the face of asymmetric information, however, parties can also send signals which may change beliefs and behavior of participants, and thus market outcomes, even when the signals convey little, or false, information.

In this paper, we study how signals designed to change beliefs about quality affect large decisions related to education. We focus on two interrelated and important markets: the market comprised of students choosing between colleges and the market comprised of employers choosing between recent college graduates. The key decision in each – which college to attend, and which candidate to hire, respectively – is made under uncertainty. College applicants cannot observe the true quality of different colleges (Deming et al., 2012, 2016; MacLeod et al., 2017; Mulhern, 2021), and employers cannot observe all traits about a potential employee (Bolton et al., 2005; Koszegi, 2014). As a result, these decisions hinge upon people’s beliefs about a school’s quality (MacLeod and Urquiola, 2015; MacLeod et al., 2017). Knowing this, colleges often attempt to send signals about the college’s quality by changing observable aspects of the college that may signal higher quality; for example, by spending large amounts of money advertising and upgrading facilities (Winter, 2003; Alter and Reback, 2014; Newlon, 2014).

The signals we study are college name changes, many of which attempt to change beliefs about college quality. College name changes are very common, both in the US higher education system and across the world. Many elite institutions of higher education have changed their names over their history: Princeton University, for example, was once The College of New Jersey, and

Columbia University was previously Columbia College, before which it was King's College. In the US, more than 530 institutions have changed their names since 1996 (Clark, 2009). These name changes aim to attract better or more students, but often correspond to little or no immediate change in facilities or resources at the year of name change (Finder, 2005; Associated Press, 2015; Belman, 2017; Clinton, 2020).¹ In China, the context we study in this paper, more than 700 colleges have changed their name since the 1990s. Among those which changed their names during our study period (2006-2016), we find no evidence of immediate changes in the resources or output of the institution at the year of the name change.² Because the value of an educational institution depends partly on who chooses to attend it, however, college quality can improve if the college recruits better students, even in the absence of any change in other fundamentals.

Our paper answers two core research questions: first, how do these college name changes affect people's decision of which college to attend, and thus the aptitude of the students the college is able to recruit? Second, how do college name changes affect the labor market performance of recent college graduates? Our analysis shows how these effects vary crucially with two factors: one, how attractive or alluring the name is; and two, the information people do, or do not, possess.

We use the case of China because of three key features which make it an ideal setting for our study. First, China has the largest market of college students in the world³ and hundreds of well-established colleges which changed their names in the last 20 years. Second, China has a unidimensional measure of applicant quality: the applicant's score on the annual college entrance exam. This allows us to precisely estimate how college name changes affect the quality of enrolled students. Finally, China's labor market is very large and, similar to the US, hundreds of millions

¹Several hundred more US colleges changed their names in this fashion between 1800 and 1950. For an excellent review of this phenomenon in the US context, see Platt et al. (2017).

²Fewer than half of the name-changing colleges we study face any legal requirement regarding college resources or staffing in order to receive permission to change their name. For many of even these colleges, the requirements are not binding, as the college has long since met them. For colleges which have not yet met these requirements, it normally takes (at least) several years to do so as part of the process of preparing the application for permission to change names, so very little changes in the year of the name change. We describe this in greater depth in Section 2.3.

³In 2019, roughly 3.89 million students graduated with a BA from Chinese degree-granting colleges. In 2019 in the US, roughly 1.98 million students graduated with a BA. Sources: Chinese Ministry of Education, http://en.moe.gov.cn/documents/statistics/2019/national/202006/t20200611_464788.html; US: National Center of Educational Statistics, https://nces.ed.gov/programs/digest/d19/ch_3.asp. Both accessed 3/27/2021.

of workers conduct job searches online, allowing us to run a large resume audit study.

We show how college applicants respond to college name changes using difference-in-differences analysis on a large administrative dataset. This dataset contains average college entrance exam scores for the students enrolled in 95% of China’s bachelor’s degree-granting colleges, summarizing the scores of over 40 million applicants from 2006-2016, a period in which more than 200 colleges changed their names.⁴ We focus only on institutions with permission to grant bachelor’s degrees, excluding those that upgraded from primarily granting three-year degrees.

We find that college name changes are successful in attracting higher-scoring applicants, and that these gains persist in the years after the name change. We estimate that a name change generates a 0.057-0.077 SD improvement in student aptitude, equivalent to an improvement of roughly 40 to 50 places in national rankings. We uncover far greater effects of college name changes in cases of greater informational asymmetry between colleges and students. First, we show that name changes which convey alluring but false information – either about the college’s location, or about other college fundamentals – have larger effects on college choice. Second, we find that all of our estimates are larger among students with less information about the college.

To learn how students actually perceive and experience these name changes, we analyze a large body of text data scraped from a major Chinese online discussion board. This analysis reveals that students often lack crucial information about colleges when making college choice. Many students also report being deceived by the college name changes we study. For example, one type of college name change – now banned by the government – led students to believe that certain colleges are located in large provincial capital cities, rather than their true location in smaller, non-capital cities.

To determine how college name changes affect students’ labor market performance, we run a large resume audit study. We submitted over 14,000 resumes to employers across six large cities in China to estimate an applicant’s likelihood of receiving a callback when listing a college’s new name, as compared to its old one. We send resumes in pairs: in each pair, both applicants will have

⁴Shi et al. (2020) use a smaller dataset (roughly 40% of the colleges we have) and a different analysis strategy to estimate how a subset of these name changes affect student quality, but do not investigate the questions of asymmetric information, resources, labor market consequences, and other topics that we engage with here. At the end of Section 3.3 we further describe how our findings relate to this and two other related studies.

attended the same college, but the college name listed varies across resumes.

Overall, we find no detectable difference between callback rates for applicants listing a college’s new name and similar applicants listing its old name, but the overall estimate masks heterogeneity in callback behavior across job types. For jobs with lower requirements for experience and technical skill – what we call “low status” jobs – we observe a significant 15% penalty in the likelihood of receiving a callback for resumes listing a college’s new name. This pattern is consistent with recent resume audit studies conducted in the US, China, and India, respectively (Deming et al., 2016; Chen, 2019; Sekhri, 2020), which find that in lower-pay or lower-status jobs, HR professionals avoid pursuing “overqualified” applicants who are difficult to recruit and retain, and who might underperform on the job because of mismatch.⁵ By contrast, in all other jobs we see a small, non-significant premium to listing a college’s new name. This estimate is precise, however, and can rule out anything larger than a two percentage point callback premium to listing a new name. In total, our results show that the labor market gains from listing a new college name, even in jobs where this is valued, are unlikely to ever be very large.⁶

To better understand what employers perceive about college name changes, we analyze two supplementary datasets: administrative data containing scores of individual test-takers in the Chinese civil service exam, and data from a survey of human resources professionals. The civil service exam data show that college name changes are coincident with an observable increase in applicant quality. The survey reveals that professionals making hiring decisions are aware of college name changes and their effects on college choice. They also believe college name changes are likely to help students in the labor market except, as we see in the resume audit data, in jobs for which the applicant may be perceived as overqualified.

Our paper makes two main contributions. First, we advance understanding of the relationship

⁵In further support of this interpretation, we find a larger new name penalty within these jobs among smaller firms and jobs which pay lower salaries (as in Chen, 2019), cases in which mismatch may be relatively costly to the employer or in which high-qualified applicants are more likely to be dissatisfied, respectively.

⁶Our resume audit study has similar or greater statistical power than many other prominent resume audit studies, such as Bertrand and Mullainathan (2004), Deming et al. (2016), and Agan and Starr (2018). Nonetheless, reducing the sample size by a factor of four for each of these comparisons increases the minimum detectable effect proportionately. Assuming that our point estimate of the premium among this latter set of jobs is the true value, estimating it precisely would have required submitting an additional 40,000 job applications to these jobs alone.

between information and school choice (c.f., Hoxby 2007; Hastings and Weinstein 2008; Hoxby and Turner 2015; Dillon and Smith 2017). Prior work has shown that, as participants/consumers gain access to more information, educational systems/markets shift in a way that improves efficiency (Andrabi et al., 2017; Dizon-Ross, 2019; Bergman, 2021). We show that, in a context of uncertainty, the dynamics of important educational systems and markets also change when participants send deliberately crafted signals designed to change the beliefs of other participants.

Second, we advance understanding of the value of signals, and names in particular, in markets with information frictions. People often use names to infer the characteristics of products and firms, and the names that firms, products, and even people are given can have large economic consequences (Tadelis, 1999; Bertrand and Mullainathan, 2004; McDevitt, 2014; Rubinstein and Brenner, 2014; Belenzon et al., 2017). We show how this phenomenon manifests in two important, interrelated markets for higher education, with applications in a wide range of contexts.

We also generate estimates of the impact of a widespread and influential policy. These college name changes have affected the college choice of tens of millions of students across the US (Platt et al., 2017; Acton, 2022), China, and other countries to date, and will affect the lives of tens of millions more in the next few decades.⁷ Our findings show that while these changes affect college choice behavior, they are also perceived in the labor market as increasing average graduate quality.

The paper proceeds as follows: Section 2 explains the setting and phenomenon we study. Section 3 presents our analysis of how college name changes affect college choice. Section 4 presents our analysis of how these changes affect early labor market performance. Section 5 concludes.

2 Setting

China's college education system had 2,688 officially recognized post-secondary degree-granting institutions in 2019, 1,265 of which were permitted to grant bachelor's degrees. It is the largest college system in the world in terms of students, handling applications of between eight and eleven

⁷Using just the US and Chinese cases, we assume that there are 500 colleges per country who have changed their names in the last 20 years. Assuming each Chinese college takes in roughly 2,000 students per year and each US college takes in between 500 and 1,000 students per year, this means that the careers of at least 25 million students were affected by these name changes, over this period, in these two countries alone.

million students per year (Yu et al., 2012). In this section, we describe the relevant institutional details of college name changes in China and how this relates to applicants' college choice behavior.

2.1 College name changes in China

China's most prestigious institutions, such as Peking University and Tsinghua University, were founded between the late 19th and early 20th centuries. Many colleges were established later, in the period immediately after the founding of the People's Republic of China in 1949. When these schools were created, they were modeled on the Soviet example with the goal of training China's elite with specific skills related to production or leadership. They granted bachelor's, master's, and doctoral degrees across a wide variety of subjects, but were often named to emphasize their contribution to national economic productivity, such as the *Sichuan College of Science and Engineering*.⁸ Many institutions initially called "college" or "institute" (in Chinese, *xueyuan*) were designed with the purpose of granting both undergraduate and graduate degrees. As a result, differentiation between the name "college" or "institute" (*xueyuan*) and the name "university" (in Chinese, *daxue*) is less informative about the offerings of the institution than it is in other contexts. This is one of many aspects of the setting which make it particularly suitable for our study.

In the 1980s, as China was transitioning from a command to a market economy, the government redirected colleges to focus on training individuals to be productive members of the new economic system. With that transition came the beginning of the name changes we study in this paper. In Figure A.1, we show a histogram with the number of name changes by year, from 1980 – when this phenomenon began – until 2019. There are 715 colleges which changed their names over this period, more than half of the 1,265 institutions permitted to grant bachelor's degrees.

The name changes we focus on in this paper occurred between 2006 and 2016. We study the set of institutions which were permitted to grant four-year degrees over this period. We exclude from our analysis all institutions which upgraded during this period from primarily granting three-year

⁸Two additional periods of college founding took place: one in the 1980s, as part of China's reform and opening, and the other in the early 2000s, as part of China's broader college expansion. During this latter expansion period, China also permitted the establishment of private colleges to meet demand for tertiary education that was not fully met by the expansion of slots at public colleges. These private colleges are widely regarded to be inferior to public ones.

degrees (in Chinese, *dazhuan*) to primarily granting four-year degrees. We also exclude institutions which merged with others over this period. The name-changing schools in our sample span the first (lowest) to the sixtieth percentile of national rankings at the start of our study period.⁹

2.2 Types of name change

There are several distinct types of name change. In Table 1 we describe these types, giving examples and indicating two additional features of the change: one, whether the college had to meet government-set resource requirements for the permission to change their name; and two, whether the change was initiated by the college itself, as opposed to being caused by forces external to the institution. The first type is the switch from “college” (*xueyuan*) to “university” (*daxue*), as studied in the US context in Clinton (2020). The second type, also common, is an increase in the implied geographic scope of the institution, usually implemented by replacing a city’s name with that of the province in which it is located, as was the case when *Xuzhou Normal University* became *Jiangsu Normal University*. As we will show, this type contains many cases in which the name provides misinformation about the geographic location of the college. A third type changes the stated scope or focus of the college, as *Zhejiang College of Education* did when it became *Zhejiang College of International Studies*. These can also be combined, e.g., changing the geographic scope and changing from college to university, as did *Zhuzhou College of Technology* when it became *Hunan University of Technology*, Zhuzhou being a city within Hunan province; we call these type 4.

These four types of name change are initiated by college leaders, usually in a bid to improve the quality of the college’s applicants. In China, college leaders are public servants appointed by the Ministry of Education or local provincial governments. Like other civil servants, their promotion is evaluated based on their performance in their current and past positions (Li and Zhou, 2005). A recent study of Chinese bureaucrats in education-related posts shows evidence of this type of career-motivated decision making and related behavior (Fang et al., 2020). Success in

⁹There is a similar and common phenomenon of college name changes in the US. These often include the change from college to university, among other changes in descriptors (Platt et al., 2017; Acton, 2022); for example, Beaver College in Maine changed its name to Arcadia University. In Appendix A we describe the similarities and differences between the two contexts. Similar changes have also occurred recently in India, the UK, and Chile, highlighting the fact that this is a widespread empirical phenomenon well beyond the Chinese context.

raising student quality is a performance metric for these bureaucrats, and a news article from 2016 documents how many of them see college name changes as a tool for career advancement.¹⁰

The final type of name change, type 5, is not initiated by the college itself, but rather caused by factors external to the institution. As part of efforts to expand college enrollment in the past few decades, the Chinese government has allowed the establishment of private, “independent” colleges (in Chinese, *duli xueyuan*) which often pay for the privilege of using existing public colleges’ names in their own names. These private colleges are generally seen to be of lower quality than the “parent” public college with which they are associated.

Type 5 name changes occur exclusively at these private colleges, and we divide these into type 5a and 5b. Type 5a name changes are caused by the parent college changing its name. Parent college name changes are not made in consultation with, and are no way dependent upon, circumstances at the private college. Because the private college is allowed to keep its link to the parent college, the signal sent by its name improves, despite two features: one, nothing about the college changes, and two, the name change was not even instigated by the college itself. In Type 5b name changes, private colleges are forced by the Chinese Ministry of Education (MOE) to drop the link to their parent college. This occurs when the private college meets a given set of standards related to the quality required of an institution for it to be given the right to grant bachelor’s degrees independently. Type 5b changes therefore cause a drop in the attractiveness of the signal sent by the new name, despite the fact that the name change corresponds to government recognition of an improvement in the underlying fundamentals of the college.

2.3 What happens when a college changes its name?

The Chinese MOE is responsible for approving college-initiated name changes. For most cases (types 2, 3, and some of type 4) there are no official requirements to be met. For cases which include the change from college to university (type 1 and some of type 4; 109 of the 244 changes we study), there are two sets of government-set standards for what constitutes a university that the

¹⁰Source: <http://cpc.people.com.cn/pinglun/n1/2016/0119/c78779-28066724.html>, accessed 9/5/2021.

institution must satisfy.¹¹ The first entails meeting minimum levels for the number of students, the quality of facilities of the college, and the number of subjects offered. These are unlikely to be binding, as most colleges are already large, have large enrollments, and offer many subjects.¹² The second entails meeting minimum levels for the qualifications of faculty, research productivity, and resources. These are more likely to be binding but, because evaluation is based on a school's performance in the previous five years, they are still manipulable.¹³ Furthermore, a college can only apply for a name change after meeting these requirements. Because name change approvals take almost a full year, and many of these changes take several years to put into place (e.g., recruiting more faculty or winning more grants), very little about even these colleges is likely to change in the year of the name change. We show empirical evidence of this in Appendix C, finding no evidence of changes in a wide range of different measures of college resources in the year in which the name change occurs.¹⁴

2.4 College admissions, student choice, and the importance of signals

College admissions in China depend on three core factors: the student's fixed-length, rank-ordered list of colleges; the student's score on the college entrance exam; and the quota from the national government which sets the number of total students from a given province, in a given track – science or humanities – that a college may admit. The college entrance exam occurs once each year. In it, all students are tested on core subjects (Chinese, math, and a foreign language) along

¹¹Chinese college name changes do not confer any new distinction of degree-granting privilege. As mentioned previously, many institutions with the name “college” or “institute” conferred doctoral degrees throughout the period we study. This differs from the US, where state- and accreditation agency-specific regulations often stipulate that a post-secondary degree-granting institution calling itself a “university” must offer graduate studies, meet stricter accreditation requirements, or provide different resources. Nonetheless, many college-to-university name changes in the US also occur without substantial changes to facilities, course offerings, or other characteristics (Finder, 2005; Platt et al., 2017; Wong, 2019; Clinton, 2020; Acton, 2022).

¹²We provide more details about these requirements in Appendix B.

¹³A recent article by a past president of Qilu University of Technology describes how the school spent over ten years working to change its name from Shandong College of Light Industry. During this time, the school took efforts – such as setting up policies to reward external funding applications – to address the two most binding requirements: resources and research productivity. Source: <https://zhuanlan.zhihu.com/p/50249046>, accessed 11/26/2020.

¹⁴Similarly, in a study of the price effects of college mergers in the US, Russell (2021) shows that at the official date of a college merger, very little changes about a college other than its name. Rather, as in our case, any major changes to facilities, offerings, or teaching quality occur one or more years before the change is announced. Clinton (2020) shows similar patterns among six name-changing colleges in Massachusetts.

with subjects specific to their track. Around the time of the exam, students also submit a fixed-length, ranked list of colleges to a national clearinghouse.¹⁵ Unlike in the US, in China the cost of “applying” to a school is therefore only the opportunity cost of occupying one of a limited number of positions on the ranked list, rather than the additional administrative costs US students face, such as fees, essays, and postage. In Section 3.3 we discuss the implications of this for our estimates.

The admissions clearinghouse matches students to colleges using province-specific assignment mechanisms; in all assignment mechanisms, students compete with other students from their province, in their track, for admission to the colleges they list (Zhang, 2016; Chen and Kesten, 2017; Jia and Li, 2021). If a student is matched to a college, they are then removed from the matching system and the process ends for them. This means that a student receives at most one offer of admission per cycle, not many offers as in the U.S. If the student chooses not to take this offer, they will not be able to attend college that year.

Chinese high school students choose colleges with imperfect information. As in the US, many dimensions of college quality are unobservable. Furthermore, students receive only suggestive information about the likely admissions cutoffs for their current application cycle¹⁶ and state their college preferences under this uncertainty. Bo et al. (2019) show that this generates substantial mismatch of students to colleges, and that relieving one key information problem – revealing students’ scores before they have to state their college preferences – reduces the probability of mismatch by 18%. Loyalka et al. (2021) show that poor and rural students make particularly sub-optimal choices reflecting limited knowledge of colleges, particularly those outside of their province.

Because of this informational asymmetry, college name changes can impact the quality of recruited students even in the absence of any other changes in college fundamentals. This comes from two sources. First, the name changes we study send alluring signals. As we document in

¹⁵The number of colleges students can rank varies from 10 to 40 schools depending on the year and province. The sequence of testing and preferences also varies somewhat across provinces and over time in our sample. Because we are comparing within years, within provinces, there is no variation in this sequence, or in the number of schools that a student can rank, within each of the cells we analyze.

¹⁶In a given year, the admissions cutoff for a given college in each province-track cell depends on the demand for that college in that cell. This varies from year to year: the mean year-on-year change of this cutoff is 5 points (out of 750) and the standard deviation of this change is 30 points (Jia and Li, 2021).

Section 3.5, many receivers parse new college names as indicating higher quality, even in cases where the name conveys little, or even false, information.¹⁷ This also relates to the literature on costly signaling, which predicts that firms will spend money on advertising to signal their type (Milgrom and Roberts, 1986; Bagwell and Ramey, 1994a) and that transmission of information in this manner can improve market outcomes (Bagwell and Ramey, 1994b). More recently, Mayzlin and Shin (2011) show that even “uninformative” advertising – signals which contain no explicit mention of new information – can be interpreted as positive signals of quality in markets when there are many competitors, such as the one we study. One corollary is that the less information applicants have about an institution, the larger is the expected effect from these signals.¹⁸

Another source of these effects is rational expectation of a possible increase in the quality of the peer group at the institution. This has a “general equilibrium” flavor to it: if an applicant anticipates that the name change may attract other applicants with higher aptitude, this is equivalent to anticipating a potential real increase in the quality of that college. In our context, such an effect could also stem (partially) from a rational belief that, since the college’s name received government approval, the signal is likely to have some element of truth.¹⁹ In addition, because applicants can observe the average college entrance exam score among students enrolled at the college in the previous year, any impact of college name changes is likely to persist over time. Indeed, work on the US higher education system suggests that this could have compounding effects over time, leading to a greater “fanning-out” of selectivity in the longer term (Hoxby, 2009).

We further characterize students’ college choice behavior using a survey of the entering class of students in the 2014-15 academic year in an anonymous, elite Chinese college.²⁰ The survey asked respondents which factor most influenced their choice of college. Other than the student’s

¹⁷Several studies show that school choice at various levels can be affected by even small doses of new information (Pope and Pope, 2009; Hoxby and Turner, 2013; Alter and Reback, 2014; Andrabi et al., 2017).

¹⁸Hoxby and Turner (2015) show that high-achieving, low-income US students lack information about “net prices, instructional resources and rigor, student bodies, and curricula.” They also highlight one common misperception particularly relevant to our study of college names in this paper: many of the students surveyed thought liberal arts colleges were politically liberal and focused on either the humanities or the visual arts.

¹⁹We note that the most egregiously misinformative name changes – those providing misinformation related to the geographic location of the college – have since been banned by the government.

²⁰This college is in the elite “Project 211” group of colleges (Yaisawarng and Ng, 2014).

CEE score, which mechanically determines admission, the school’s reputation (*shengwang*) was the most common factor given, with 337 of the 2,611 respondents selecting this.²¹

3 How college name changes affect college choice

In this section, we study how college applicants respond to college name changes. Using a difference-in-differences research design, we estimate how the aptitude of students choosing to enroll at a given college – as measured by their CEE score – changes with a name change, compared to essentially all other colleges in the market for these applicants. We also analyze scraped text data from China’s main Q&A website to illustrate what applicants believe about college name changes, and how these beliefs compare with what they encounter when they arrive at college.

3.1 Data

We use administrative data on the college entrance exam scores of students entering each college from each province, by track and by year, from 2006-2016. Our data covers 95% of Chinese colleges and comprises roughly 420,000 data points, summarizing scores from approximately 40 million students. Henceforth, we will refer to these as “CEE” scores (in Chinese, *gaokao* scores). These data were scraped from a leading educational website, “China Education Online” (www.eol.cn), the administration of which is supervised by China’s Ministry of Education.

These data contain the average and maximum CEE score, by year and by the home province of students, for all enrolled students in the science and the humanities track, respectively, in each college.²² In some of these cells, there are two tier-specific observations, reflecting the fact that at a given school, some majors within a track may be of higher status (tier) than others.²³ Because test questions vary each year and, within a year, vary across provinces and across tracks, we standardize

²¹In this and another survey of college students in various colleges administered in 2009 (the *daxuesheng chengzhang zhuzhong diaocha*, or “CSDPS”), respondents were asked who was the most important influence in their choice of which college to attend. Roughly half of students (~48%) in both surveys listed themselves, followed by parents or other family members (35-40%), and then teachers, friends, and other non-family members.

²²Recall that students in a given track only compete for admission with other students from the same province.

²³Over this period, each major-track-college-province cell was assigned to one of three tiers. Admissions in each cell are subject to students meeting a tier-specific minimum CEE score set by the Ministry. In most cases this is not binding, as the minimum score at a given institution is determined primarily by the demand for that particular college-track-tier combination in that year.

test scores at the province–year–track level. We limit our analysis to colleges that are qualified to issue bachelor’s degrees²⁴ and non-military colleges. This leaves 1,198 colleges in our analysis sample, comprising roughly 95% of the 1,265 bachelor’s degree granting institutions in China. In Table A.1, we present summary statistics about the colleges in our sample and their name changes.

To identify the incidence and timing of college name changes, we hand-coded information posted on college websites and on the website baike.baidu.com, a Chinese analogue to Wikipedia.com. Among the 1,198 colleges in our analysis, 244 colleges (20.4%) changed names between 2006 and 2016. We also gathered enrollment quota data at the province–year–track level from 2008 to 2015 from another leading educational website in China to use in our robustness analysis.²⁵

3.2 Empirical strategy

We use a difference-in-differences design to estimate whether the aptitude of students who choose to enroll at a given college, as measured by their average CEE score, changes after the college changes its name. We regress the average CEE score within a college–province–year–track–tier cell on an indicator for use of a new name, along with a set of fixed effects as controls. The coefficient on this indicator variable estimates the difference in score within colleges, across the old name–new name threshold, as compared to the rest of the market for college applicants.²⁶ Our main estimating question is:

$$y_{cpstr} = \beta_0 + \beta_1 NewName_{ct} + \beta_2 s_{cptr} + \theta_c + \mu_t + \eta_p + \tau_r + \varepsilon_{cpst} \quad (1)$$

The variable y_{cpstr} is the mean CEE score for students entering a given college c , from a given province p , in a given track s (science or humanities), in a given year t . As described above, in some cases, there are two observations – one per tier r – within a college-province-track-year cell. We cluster our standard errors at the college-province-track level, the level at which there is most likely to be autocorrelation in our error estimates.²⁷

Our main coefficient of interest is β_1 , the impact of a new name on the average CEE score of

²⁴The market for associate’s degrees is a separate market of interest left to future research.

²⁵The website – <http://www.gaokao.com/> – also focuses on China’s college entrance examination.

²⁶As a result, our recovered estimates will be closer to the general equilibrium effect of a name change, i.e., after all market interactions in response to the name change occur, as opposed to the partial equilibrium effect.

²⁷Our main results are robust to instead clustering at the (more conservative) college level.

students who enroll at the college. The variable $NewName_{ct}$ is an indicator for the college having changed its name and is equal to one in all years after the change. Five sets of controls are central to our identification strategy. The first is the set of fixed effects at the college level, θ_c , to ensure that we are comparing only within a given college, across time. The second is the set of year fixed effects, μ_t , which removes variation from time trends secular to changes in college names. The third is the set of province-level fixed effects, η_p , which ensures that we are comparing only among applicants from within a given province, the level at which applicants compete.²⁸ The fourth is the control for whether a given score is from the science track, s_{cptr} , as opposed to the humanities track, included because students compete within tracks, and scores are standardized at the province-year-track level. Finally, within a college-province-track-year cell, different majors may sometimes be in different tiers. We control for tier fixed effects, τ_r , because, within a college and within a track, majors in different tiers have different minimum score requirements.²⁹

Our main identifying assumption is the standard parallel trends assumption. Here, since our main comparison is of name-changing colleges to the entire market, for identification we need that the scores of the “treated” group exhibit parallel trends relative to the rest of the market of colleges vying for college applicants. Given that there are many different treatment years, we assess this primarily through the (stacked) event study, in which we plot point estimates and confidence intervals derived from replacing the $NewName_{ct}$ variable in equation 1 with a series of indicator variables for the number of years elapsed since the college’s name change:

$$y_{cpstr} = \alpha_0 + \sum_{T=-9}^9 \alpha_{1\#T} NewName_{Tct} + \alpha_2 s_{cptr} + \theta_c + \mu_t + \eta_p + \tau_r + \varepsilon_{cpst} \quad (2)$$

As we discuss in the next section, this shows no evidence of a statistically significant difference in test score trends prior to changes in college names. In Figure A.2 we show an alternative test of this, using the method in de Chaisemartin and d’Haultfoeuille (2020). Similarly, this figure reveals no evidence of violation of the parallel trends assumption.

A series of recent papers have shown that difference-in-differences estimates of policies or pro-

²⁸All of our results are robust to multiple alternative fixed effects specifications, described in the next section.

²⁹Tier and name change in the same year in only 380 of the 10,514 treated college-province-track cells. Our results are all also robust to the exclusion of these cells.

grams with staggered rollout may suffer bias from negative weights assigned to some components when implemented with a two-way fixed effects-style approach, such as the one we specify here (Callaway and Sant’Anna, 2019; de Chaisemartin and d’Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). In Appendix D, we conduct a series of robustness checks to assess the risk of this type of bias. We conduct the decomposition proposed in Goodman-Bacon (2021) and the calculation of negative weights proposed in de Chaisemartin and d’Haultfoeuille (2020), which show our application has a small proportion of negative weights, and that these contribute very little to our overall estimates. We also show that our estimates are robust both to the exclusion of these components, and to the use of two alternative estimators from de Chaisemartin and d’Haultfoeuille (2020) and Borusyak et al. (2021), respectively.

3.3 Main results

In this section we present our estimates of the effect of college name changes on the average CEE scores of students choosing to enroll at name-changing colleges, as compared to the rest of the market for these students. We also present a series of robustness checks.

In Table 2 we present two estimates of our main parameter, β_1 from Equation 1: in column 1, we show our estimate of the effect for all name-changing colleges, and in column 2, we show our estimate for those colleges whose name change contains a shift from the word college (*xueyuan*) to university (*daxue*). In column 1 we estimate that after a college changes its name, the average CEE score of the students who choose to attend the college increases by 0.057 SD. In column 2, this estimate increases to 0.077 SD, suggesting that these colleges harvest an additional benefit from adding the word “university” to their names.³⁰

These results translate into a real gain in national rankings, and are similar in magnitude to other studies of how positive shocks to college reputation affect the quality of recruited students. For example, we can calculate the equivalent gain in national rankings from the estimates presented in Table 2. To generate this, we estimate Equation 1 with college rank as the dependent variable

³⁰Table A.2 reproduces Table 2, also presenting estimates of β_2 and τ_r . In Table A.3 we show these results are robust to replacing college, province, and track fixed effects with fully interacted college x province x track fixed effects. They are also robust to using province-by-year fixed effects instead of province and year fixed effects separately.

and average CEE score as the main explanatory variable. We find that the overall impact of a name change is equivalent to a rise of roughly 40 places in the national selectivity rankings, and a change from college to university yields a 50-place rise.³¹ We can also compare our results to similar estimates of how salient, positive information about US colleges increases the academic aptitude of applicants to the college and of the students it ultimately recruits. Pope and Pope (2009) find that high-visibility successes of college sports teams increase the number of applications to the college by students with high SAT scores. Alter and Reback (2014) show that a college appearing in the US News and World Report college rankings, or increasing its rank on that list, increases the academic competitiveness of enrolled students at the college relative to the college’s competitors. While neither study has outcome variables that are directly comparable to ours, the sign and order of magnitude of their estimates align with our main findings.

In Figure 1, we plot the event study version of the results shown in Table 2. In Panel A, we present the event study for column 1 and, in Panel B, that for column 2. In both, our estimates of $\alpha_{1\#T}$ for years prior to when a college changes its name are indistinguishable from zero and their gradient is flat, suggesting that the parallel trends assumption is satisfied. After the name change, we estimate an immediate increase in $\alpha_{1\#T}$ that is sustained over time.

A series of robustness checks show the stability of our results to several alternative explanations. First, we estimate how CEE scores vary over time among colleges whose initial applications to change their names failed. We located records for nine such colleges containing the year in which the college’s initial application to change their name was denied, along with the year in which they reapplied and were successful.³² We generate two estimates of β_1 from Equation 1 for these colleges: first, using the “failed treatment year” as the year after the application year, i.e., when the name change would have been approved had it not failed, and second, using the year in

³¹In Figure A.4 we show our estimates of heterogeneity by college rank. We also show estimates of heterogeneity in effects by track and tier in Table A.4; we find larger effects for lower-tier colleges but no difference by track.

³²While we do not know the reason for failure, in some cases, the proposed new name was seen to be controversial and opposed by other colleges. For instance, Tangshan College (*Tangshan Xueyuan*) attempted to change its name to Tangshan Jiaotong College (*Tangshan Jiaotong Xueyuan*) in 2018 but failed. This failure is attributed to the fact that the new, proposed name was historically used by other colleges, including Southwest Jiaotong University and Xi’an Jiaotong University (source: <https://www.cingta.com/detail/4390>, accessed 11/26/2020).

which the change was ultimately approved. We report these results in Table A.5. For the failed treatment year, we estimate $\beta_1 = 0.001$ ($se = 0.012$). For the subsequent, successful name change on CEE scores among these colleges, on the other hand, we estimate $\beta_1 = 0.030$, ($se = 0.011$). Second, we conduct the same two regressions from Table 2, only replacing our main outcome variable, the average CEE score of admitted students, with the maximum CEE score among admitted students within a cell. This provides additional information about whether the change attracts marginally or globally better students. Our coefficient estimates maintain their sign and significance, and their magnitude increases (see Table A.6). This suggests that the college choices of high-aptitude students were affected by name changes, as well as those of the modal student.

Third, we show that our results are not driven by a change in the enrollment quota set for the school. If the school obtains a smaller enrollment quota after its name change, this would artificially inflate the school's average CEE scores, as it would force the school to deny admission to lower-scoring applicants who would have gained admission were there the previous, larger quota.³³ Our results are robust both to adding the enrollment quota as a control and to using the original specification, but restricting the sample to only colleges with non-missing quota data (Table A.7).³⁴ Fourth, we show that these patterns also appear in individual-level data from Chinese high schools. We present these in Table A.8, and find similar patterns, with a significant, positive impact of name changes on the average score of enrolled students, and a larger effect for institutions whose name change includes the switch from college to university.

Because students submit a ranked list of schools of fixed length, our results may not capture the full effect of college name changes on college choice. While we are unable to observe the rank-ordered lists of applicants, if students feel obligated to “fill” the end of their lists with college

³³In fact, it is more likely for a school to obtain a larger (rather than a smaller) enrollment quota after its name change. Specifically, because a school with a new name is more likely to experience greater demand from students, it is thus more likely to obtain a larger enrollment quota from the Ministry of Education. If this occurs, our estimates are likely to instead *under*-estimate the effect of college name changes on the quality of enrolled students as, *ceteris paribus*, a greater number of slots would lead to a lower average score of entering students.

³⁴A potential confounder related to quotas is China's affirmative action policy for college admission, the “National Special Plan,” which provides preferential treatment via extra CEE points to high school graduates in poor regions of the country applying to top universities. There are 95 Chinese universities who participated in this plan in 2021, all of which are top-tier universities (985-project or 211-project universities), and none of which changed their names during our sample period. As a result, this policy is unlikely to confound our estimation.

names for which they have less information than those listed at the top of the list, our results would provide a lower bound of the true effect of college name changes on college choice. This comes from two sources: one, we would expect even larger effects of name changes on the ranking of college preferences further down a person's ranking list, when they may have exhausted their list of known colleges and be inclined to list more appealing-sounding but unknown schools (Loyalka et al., 2021); two, the nature of the clearinghouse process means that students' lower ranked choices are less often reached. While evidence from the US shows that students may leave many slots blank in their rank-ordered lists (Corcoran and Levin, 2011; Corcoran et al., 2018), the proportion of blank slots on the list of an average student in China is far lower (Chen et al., 2020).

Finally, in Appendix E, we decompose the effect of name changes into two components: one, the gain colleges enjoy by attracting students from competitor colleges, and two, the gain in student quality that comes from attracting students who otherwise would have gone to more selective colleges. Our estimates suggest that roughly 75% of the gain comes from component one, with the other 25% coming from component two.

Three recent papers also study these topics. Shi et al. (2020) uses a different dataset to study a narrower set of questions related to the impact of Chinese college name changes on the ability of institutions to attract more qualified applicants. It finds no evidence of an overall effect of college name changes, but a significant positive effect for colleges whose name changes include the shift from college to university and for those which contain other appealing changes, similar to some of those we study in the next section. We believe our findings diverge because we study far more of the market (1,198 out of 1,265 BA-granting institutions; that paper analyzes only 552), allowing us to estimate effects for lower-ranked colleges whose name changes do not include the change from college to university. Clinton (2020) shows how the change from college to university among six universities in Massachusetts led to greater earnings of graduates. In Section 4, we show a related parameter - how college name changes affect likelihood of receiving an initial callback from a job application. Acton (2022) studies how revenue and the *number* of recruited undergraduate and graduate students vary before and after a name change among colleges in the US. We instead focus

primarily on how the *aptitude* of the students who choose to enroll in a given college responds to different types of name change, alongside impacts in the labor market.

3.4 Alluring signals and access to information

In this section, we study two phenomena that reveal the importance of college–applicant informational asymmetry in generating the effects we measure in the previous subsection. First, we generate estimates for two sets of name changes in which the signal sent is alluring, but is either misinformative or contains no information about the college’s resources; these changes comprise a change in signal without a corresponding change in fundamentals. Second, we show how our estimates vary with the information different applicants have about name-changing colleges.

In Table 3, we present two sets of estimates of the effects of alluring but misleading name changes on college choice. First, in Panel A we estimate heterogeneity in the effect by whether the name change includes misleading information about the geographic location of the college. In our data, 45 name-changing colleges include wording in their new names which suggests that the college is either a province- or national-level institution, a type of change that would be categorized as type 2 in Table 1. Because of linguistic custom, these names imply that the college is located in a provincial capital, but in reality none of these 45 colleges are located in the capital of their province. The practice was so misleading, in fact, that it has since been banned by the government.³⁵ We find that these alluring but misleading name changes have a much larger effect on CEE scores than other types of name changes. Our point estimate for the effect of these name changes (column 1 of Panel A) is nearly twice the magnitude of that for all other changes (column 2), and we can reject the equality of the two estimates with a high level of certainty ($p < 0.001$).

In Panel B, we study the impact of name changes among private colleges. These changes – types 5a and 5b in Table 1 – were initiated by a third party and send a similarly misinformative signal. For type 5a, the parent public college changes its name, giving the private college a new name with a better signal. For type 5b, the private college is forced to remove the link to the parent

³⁵These misleading geographical name changes were specifically prohibited by “A temporary regulation on naming colleges” (http://www.gov.cn/zhengce/zhengceku/2020-08/31/content_5538872.htm; accessed 7/21/2021).

college in its name, sending a potentially negative signal about the college despite the name change corresponding to government recognition of an improvement in the quality of the college.³⁶

As a result, our estimates for type 5a and type 5b name changes show the impact of a change in signal without any positively correlated change in fundamentals. Type 5a changes send a positive signal with no change in fundamentals. Type 5b changes send a negative signal despite official recognition of better fundamentals. The signs of our estimates correspond to the signal sent by the name change: we estimate a large, positive effect for the positive signals sent by type 5a changes (column 1), and a negative effect for the negative signals sent by type 5b changes (column 2).

Next, we ask how the effects of college name changes vary with the information applicants have about the college. Following Loyalka et al. (2021) and MacLeod and Urquiola (2019), we assume that within-province applicants know more about their province's colleges than they do about colleges further afield, and we compare estimates of β_1 from Equation 1 for students from within the same province in which the college is located to those for students from outside of the province. We show three sets of related results in Table 4. In Panel A, we show the estimates for out-of-province students and within-province students, both for all name changes and for the change from college to university. This reveals two patterns, both of which suggest that these signals have greater impact among applicants with less information. First, the out-of-province effects are much larger than the within-province effects. Second, for out-of-province applicants the college-to-university effect is much larger than the overall name change effect. For within-province students, however, we cannot reject that the effect for all name changes is the same as for college to university changes, and the confidence interval excludes anything larger than a 0.005 SD difference.³⁷ In other words, the additional effect of the college-to-university change disappears among applicants who have more information about the name-changing college. Finally, in Panels

³⁶In 2021, students in Jiangsu and Zhejiang protested this type of change and the threat of the negative signal it would send: <https://www.scmp.com/news/china/article/3138919/chinese-student-protests-putting-independent-college-merger-plans-hold>, accessed 2/2/2022.

³⁷We also conduct a related analysis, dividing the sample into colleges located in large cities and colleges located in small or medium-sized cities. The intuition behind this comparison is that colleges in larger cities operate in an environment with more people and more flow of information than colleges located in smaller cities. We show these results in Table A.9; as predicted, the effect of a name change is much larger among colleges located in small or medium-sized cities than those located in large ones.

B and C of Table 4, we show that the alluring-but-misleading signals studied in Table 3 have greater impact among out-of-province applicants than among within-province applicants.

3.5 What students see and believe about college name changes

Next, we analyze text data scraped from a major website containing online discussions about college name changes. We use these data to characterize what college applicants believe about college name changes and how this may influence college choice. Our findings suggest that the results in Sections 3.3 and 3.4 stem primarily from the informational asymmetry channel, as described in Section 2.4. By far, the most common topic of discussion we observe is discussion of the potential for applicants to be misled by college name changes, with accompanying accounts of many students who were so misled. In many other threads, students express surprise at the disconnect between the resources and features implied by the new college name and what they encounter upon arrival at the college.

We analyze text data scraped from the website www.zhihu.com, the largest Q&A platform in China. The site's format is similar to the popular website quora.com, where users post questions and other users can post responses to them. We collected these data by web-scraping the site for questions related to the name changes of specific colleges, yielding roughly 3,000 discussion threads. We then read each thread to gain intuition about what was being discussed, collect relevant anecdotes, and identify keywords for subsequent analysis. We further analyze these data using the Baidu Sentiment Analysis AI platform to estimate whether the sentiment contained in each of the discussions was positive or not. In this section, we present an overview of our results. We describe the details of data collection and present several additional analyses in Appendix F. In Table A.10, we provide several illustrative vignettes from these data.

Consistent with the first potential source of our effects, issues surrounding information asymmetry were the most frequently discussed topic in these text data. Keywords related to information (or lack thereof) appear in over 330 threads, or 11.2% of the 3,000 discussions. These contain dozens of cases which corroborate our findings earlier in this section: several discussions included assertions that students from outside of the province in which a college is located were more likely

to be “cheated” or “fooled” by name changes; in Table 4, we estimate larger effects of college name changes on college choice for this group. In another set of threads, students reported that they incorrectly inferred the location of the college from its name, corresponding to results in Panel A of Table 3 and Panel B of Table 4. Other users reported that they applied to private colleges because of their affiliation with a famous parent college, consistent with results in Panel C of Table 4.

The second-most common type of discussion was about how new college names affect the average CEE scores of students who choose to enroll at the college. More than 150, or 5.0%, of the 3,005 threads in our data explicitly discuss this topic. The vast majority (140) include assertions that new college names lead to higher CEE scores among enrolled students, especially for out-of-province applicants. The large volume of these threads is consistent with both the informational asymmetry and the rational response channels. The fact that many of these threads mentioned that the effects were particularly pronounced among out-of-province applicants, however, together with the other facts we report – see also the vignettes in Table A.10 – suggests that the informational asymmetry channel is the most important driver of the effects we measure.

We next analyze which discussions received the most attention, as measured by comments and likes. We find that the discussions which received the most attention were related to changes from college to university and, separately, private colleges whose name change severed ties to the parent public college. Both topics had roughly 20% more comments and “likes” than others. We find, however, that the sentiment around these two topics diverges. Discussions about changes from college to university had positive sentiment and were associated with putative success in raising CEE scores; sentiment in discussions surrounding private colleges whose name change severed ties to the parent public college was instead highly negative (see Table F.2 in Appendix F). The vignettes in Table A.10 illustrate, often colorfully, how new names attract these students, how students are fooled by alluring but misleading name changes, and the discrepancy between the signal sent by the name and the reality the person experiences upon arriving at the college.

These text data show that problems of information asymmetry occur for students choosing to attend a wide variety of colleges. The threads discussed 226 distinct name-changing colleges. As

would be the case in analyzing data from US Q&A sites such as quora.com, our analysis of these data is not meant to be representative of the experience of all Chinese college applicants. Rather, we argue that they show existence of the problem of asymmetric information in the process of college choice among applicants to hundreds of name-changing colleges in China.

4 How college name changes affect employer recruitment

In this section, we study how employer recruitment behavior responds to college name changes. We report results from a large resume audit study, comparing callback rates for similar resumes that differ by whether a college's old or new name is listed. We then analyze administrative data from China's civil service exam and data from a survey of HR professionals to understand employer beliefs about college name changes and how this relates to recruitment decisions.

4.1 Research design of resume audit study

We designed and conducted a resume audit study to estimate whether recruiters respond differently to job applicants listing a college's new name, relative to those listing its old name. We also designed our study to measure heterogeneity in this parameter by traits of the job and employer.

The size, distribution across sectors, and online nature of the Chinese labor market facilitate our study: China has the world's largest labor market, with 775.9 million people officially employed as of 2018 (Ministry of Human Resources and Social Security of the People's Republic of China, 2019a). Since 2012, more than 80% of these workers have been employed in the private sector (Li et al., 2012), and approximately 76% of job openings are currently posted online (Ministry of Human Resources and Social Security of the People's Republic of China, 2019b).

Our study design follows the structure of several recent resume audit studies (Darolia et al., 2015; Deming et al., 2016; Agan and Starr, 2018). To each job, we sent a pair of similar resumes, and registered whether each resume received a callback. In each pair of resumes, one lists a given college's new name, and the other its old name.^{38,39} We sent nearly 7,500 pairs of resumes to

³⁸We used only colleges whose name change was from college to university; the list of these colleges, with each college's old name, new name, and date of name change, is given in Table A.11. Using the CEE data described in Section 3, we estimate the impact of these colleges' name changes on CEE scores to be a 0.07 SD increase, similar to our estimated effect of college-to-university name changes on CEE scores reported in column 2 of Table 2.

³⁹We used only colleges which allow us to plausibly list either the new or old name based on date of enrollment and

employers across six cities in China between November 2018 and November 2019.⁴⁰

We identified jobs via search on the two largest Chinese job posting websites: 51job.com and zhaopin.com.^{41,42} We restricted our focus to jobs meeting criteria related to industry, years of work experience, and city. We focused on jobs in two industries – computer programming and human resources/administration (in Chinese, xing zheng)⁴³ – for two reasons. First, there was high volume of job postings and applicants in both; in fall 2018, for example, they were among the top six occupations in China by number of postings and top three by number of applicants.⁴⁴ Second, they differ by skills required and average pay, with programming jobs paying more and requiring demonstrable technical skill in a programming language. Similarly, we focused on two levels of required work experience: up to two years, or three to five years of experience, respectively.⁴⁵ The motivation for this choice was similar: jobs requiring more years of experience pay more, and applicants also have more years of experience on which to be evaluated. We focused on jobs in six cities – Hangzhou, Hefei, Shanghai, Wuhan, Xi’an, and Zhengzhou. Each of these cities is located in a province with two colleges which changed their names in the last five years, each has a large labor market, and, together, they are representative of China’s three main geographic regions.⁴⁶ Finally, we varied whether the resume pair used a college in the same province as the job being applied to, or in the province of one of the other five study cities. This allows us to test for the possibility that recruiters who are more familiar with nearby colleges who change their name respond differently than those from far away who may be less familiar with the college.⁴⁷

We created resumes using realistic applicant characteristics based on publicly available re-
graduation. In the resumes listing two years of experience, the colleges we used changed their names in 2016 or later; for resumes listing five years of experience, we used colleges which changed their names between 2012 and 2015.

⁴⁰This comprised 14,976 resumes, or 60% more than the 8,914 studied in Darolia et al. (2015), 35% more than the 10,484 in Deming et al. (2016), and similar to the 14,637 studied in Agan and Starr (2018).

⁴¹According to https://www.sohu.com/a/155316030_182188, accessed 1/2/2019.

⁴²These were previously used in another large study of China’s labor market (Kuhn and Shen, 2013).

⁴³Deming et al. (2016) also focus on two industries. Given the skill-specific nature of postings for programming jobs, we focused on advertisements looking for programmers skilled in the java language.

⁴⁴According to <https://www.hroot.com/detail.aspx?id=9383823>, accessed 1/15/2019.

⁴⁵Resumes submitted to a given job listed the appropriate number of years of experience as per the job posting.

⁴⁶Eastern region: Shanghai, Zhengzhou. Central region: Hangzhou, Hefei, Wuhan. Western region: Xi’an.

⁴⁷Due to evidence of explicit gender discrimination in many labor markets in China (Kuhn and Shen, 2013; Kuhn et al., 2018), all resumes within each job type were of the same gender: only resumes listing male names were submitted to jobs in programming, and only resumes listing female names were submitted to jobs in administration.

sumes posted on those two job sites. Each resume lists the name, email address, phone number, work experience, skills, and biographical information for the applicant.⁴⁸ We used two pairs of resumes for each potential combination of industry, experience level, city, and relative location, comprising a total of 192 resumes.⁴⁹ Before finalizing the resumes to be used in the study, each resume was vetted by a team of HR professionals to assess appropriateness of the resume for that type of job posting, and that the two resumes in each pair were similarly desirable from the perspective of the employer.⁵⁰

Our initial sample size was 14,976 resumes to be submitted in 7,488 pairs, with a goal of roughly equal distribution across the cells described in the previous section. We discard 412 pairs of resumes (5.5% of the total) because of three types of error: one, more than one pair was submitted to the same posting; two, the posting was taken down between the time when the first resume was submitted and the scheduled time for submission of the second resume; or three, the resumes submitted to the job were accidentally from different pairs. In addition to data on callbacks, we also collected the following data from the text of each job posting: salary, number of employees at the company, minimum required degree, and the type of company (e.g., private company or publicly listed company).

⁴⁸We created resumes using realistic applicant characteristics based on publicly available resumes posted on those two job sites. We first populated a data pool of potential work experience for each [job type–experience] meta-cell with the work experience listed on resumes taken from a corpus of resumes collected online. We then randomly assigned experience entries from this pool to populate each resume.

⁴⁹Applicant information had to be manually entered onto the website’s user interface before we could deploy the applicant’s resume to jobs. Our job applications then proceeded as follows: every day, each member of a team of research assistants was given a quota of jobs to find in a given city within a given industry (programming or administration) and a given required experience level (two years or three to five years). They confirmed the appropriateness of the job, then began the submission process. First, they submitted one resume chosen from the pair by random number generator. After at least 12 but no more than 36 hours, they submitted the second resume.

⁵⁰Since the two resumes we submit to a given posting are very similar, one concern is that recipients might suspect the applications were fictitious. Empirically, our data suggest that this possibility is very slim. First, the job experience and skills listed vary between the two resumes; second, we built in at least 12 hours between submission of the first and second resume to ensure they do not appear adjacent to each other in order of receipt; third, in only two cases of the over 14,000 applications we made were applicants contacted by an HR professional with such a doubt; finally, our overall callback rate is more than 13%, demonstrating that these resumes were taken seriously.

4.2 Results

We calculate our pre-specified, primary outcome using a simple comparison of means: we estimate a two-sample t-statistic testing the null of equality of callback rates between resumes listing an old college name and those listing a new college name.⁵¹ Because our sample is, by construction, balanced on observables, we do not control for additional differences in our primary specification. Our pre-specified heterogeneity analysis conducts similar t-tests on subgroups of the data.

We show our first set of results in Table 5. This presents mean callback rates for resumes listing old college names and new college names, respectively, their difference, this difference as a proportion of the old name callback rate, and the p-value of a test for their equality. The mean callback rate for all resumes was 13.6%.

The difference between mean callback rates for new name and old name resumes is 0.33 percentage points. This difference is not statistically significant; the p-value for the comparison of means is 0.573. Our study was powered to detect a minimum difference of 1.15 percentage points in callback rates, from a baseline of 10% of old name resumes receiving callbacks. The confidence interval around the true estimate excludes anything larger than a 1.46 percentage point difference, or a 10.6% difference of the old name average, which is a 13.8% likelihood of receiving a callback.

We find that the new name/old name difference in callback rates varies by years of experience and job type, but not by whether the job is in the same province as the college or not. Among jobs requiring two years of experience, we observe a penalty for listing the new name: the callback rate for resumes listing the college's old name is 1.51 percentage points higher than for those listing the new name ($p = 0.062$). Among jobs requiring three to five years of experience, there is a small premium of roughly 0.98 percentage points for resumes listing the new name; this difference is not statistically significant ($p = 0.234$).⁵² For jobs in administration, there is again a new name

⁵¹We registered a pre-analysis plan for this part of our study at socialscienceregistry.org, AEARCTR-0003669.

⁵²Note that experience is collinear with time elapsed since the college changed its name; the diffusion of information over time may also generate a difference in old name/new name callback rates. We anticipate both effects to push in the same direction: as time elapses, we expect less of an impact of the name change, both because people will have more time to familiarize themselves with the name change, and because for candidates with more work experience, the relative importance of the name of the candidate's college decreases.

penalty of roughly 1.5 percentage points, also on the margin of statistical significance ($p = 0.070$). For jobs in programming, there is a small, statistically insignificant new name premium (0.83 percentage points; $p = 0.29$). For both the within-province and out-of-province subgroups, the difference in the callback rate between new name and old name resumes is much closer to zero. Neither difference approaches statistical significance. We interpret this as evidence that employers have more information about college name changes, and this information does not vary by whether a name-changing college is located in or outside the province.

Our estimates of heterogeneity by experience and by industry both suggest that resumes listing a college's new name face a penalty in lower-status and lower-pay jobs. This aligns with a stylized fact from three large resume audit studies in the US, China, and India, respectively: there can exist a penalty, in certain jobs for resumes which list traits that signify higher applicant quality (Deming et al., 2016; Chen, 2019; Sekhri, 2020). This penalty arises when the recruiter has reason to believe that the applicant is overqualified for the job being applied to, as this "mismatch" raises two concerns: one, that it will be difficult to successfully recruit or retain the applicant; two, if these employees join the firm, they will under-perform due to dissatisfaction with pay or job status. These studies show that recruiters in such situations may prefer resumes without signals of mismatch to avoid the negative consequences of pursuing mismatched applicants.

Given these patterns and the results of the three prior audit studies, we further probe this possibility with a series of exploratory analyses. We first estimate callback rates across the interaction of required years of experience (two or three to five) and industry (administration or programming). We show these results in Table 5; the table presents a parameter we call α , defined to be the difference in callbacks between resumes listing a college's new name and resumes listing its old name. We also show α as a proportion of the callback rate for resumes listing the college's old name, and the p-value for a test of the null that $\alpha = 0$.

We find a statistically significant negative estimate of α for jobs in administration requiring two years of experience. In these jobs, new name resumes are 3.3 percentage points (15.4%) less

likely to receive a callback.⁵³ These jobs have the lowest status and lowest pay of the jobs we consider; the average listed salaries for these jobs are at least 55% smaller than for the other three job types. In all other jobs, new name resumes are 6-10% more likely to receive a callback. We can reject the equality of α between jobs in administration requiring only two years of experience, and all other jobs, at a very high level of precision ($p = 0.0015$).

While our estimates for the new name premium in higher-status, higher-pay jobs are not statistically significant⁵⁴, they are precisely estimated. The confidence intervals around each estimate rule out anything greater than a two percentage point difference in callbacks. These can exclude all but one of the several dozen significant estimates of premia found in two recent, similarly-powered resume audit studies (Deming et al., 2016; Agan and Starr, 2018).

We report additional exploratory analysis of the new name penalty among jobs in administration requiring only two years of experience in Table A.12. We show that there is a greater new name penalty when there is greater risk of mismatch, due either to traits of the job (lower pay; jobs not requiring a bachelor's degree), of the firm (private as opposed to publicly listed firms; smaller firms), or of the applicant (a higher ranked the college listed in the resume). Each of these results is consistent with what we would expect to see if recruiters were trying to avoid pursuing applicants they are likely to perceive as over-qualified.

This also corresponds to similar patterns seen in other resume audit studies, both from China and India. Chen (2019) reports a resume audit study comparing callback rates for applications to jobs in China. In that study, resumes vary by whether the BA-granting institution was in the US or China. It finds a penalty for applicants listing US colleges, particularly at jobs with lower salary or other requirements. It interprets this as evidence of “employers fearing U.S.-educated applicants have better outside options and will be harder to hire and retain.” Sekhri (2020) finds similar results using administrative data from graduates from elite colleges in India.

⁵³This is still significant when using a Bonferroni correction for multiple hypothesis testing, which would divide the traditional level of 0.05 by 4, yielding a threshold of 0.0125.

⁵⁴Bundling the resumes in these three cells into one, we estimate $\alpha = 0.0080$, $se = 0.0063$. Assuming that this is the “true” parameter value, we would need to have a total of 49,412 resume submissions, or roughly 40,000 more than we currently have, to generate a statistically significant estimate at the 5% level, assuming 80% power. This is five times as many as in Deming et al. (2016) and more than three times as many as in Agan and Starr (2018).

An alternative explanation for the new name penalty we observe for these jobs is that because recruitment for a lower-paying job has lower financial stakes for the company than for a higher paying job, employers for these jobs do not bother to look up the listed college. While possible and consistent with one of the other potential interpretations suggested by Chen (2019), in the next section we present evidence that this is less likely than the over-qualification explanation.

We note that the callback behavior we capture is only the first stage of a much longer recruitment process. Speaking to a group of HR professionals who are involved in this work, we learned that professionals in this type of role will be expected to examine and vet hundreds of resumes each day. This feature is important, as our results capture the differences in callback rates for two resumes with the same amount of experience listing two different names of the same college. We made this decision deliberately, both to avoid confounding the experience premium with new name effects, and because this phenomenon of applicants who graduated from the same name-changing college in the same year, but listing different college names, appears in reality. More specifically, in the civil servant exam data analyzed later in this section, we observe hundreds of pairs of students who appear to have graduated from the same institution in the same year, where one lists the institution's old name and the other lists the new name.

We argue that it is unlikely for the professional to have the time to search for and confirm i) whether a given school had changed its name, ii) if so, in what year, and iii) whether the person listed on the resume entered the school before or after the name change. Rather, we anticipate that, as described in Clinton (2020), they will simply look at the college name and infer the school's status from various markers – e.g., college vs. university – taking into account the selection effects we estimate in the previous section. In the next section, we use a series of other data sources to better characterize what recruiters see about these applicants and how they perceive the college name change phenomenon when making their recruitment decisions.

4.3 Employer beliefs about and experience of college name changes

In this section, as in Section 3.5, we analyze data which contain information on the beliefs of consumers. Here the consumers are employers choosing between candidates, and we wish to

know what they observe and believe about graduates of name-changing colleges.

We report analysis of two datasets. First, we analyze administrative data from China's civil service exam containing candidate performance on a written aptitude test. We compare performance between those graduating from a given college after it changed its name and those graduating before. Second, we analyze survey data from HR professionals, describing their subjective beliefs about college name changes and how they relate to applicant quality.

We first analyze publicly available administrative data reporting individual test scores from the written part of China's civil service exam. We see that, from the observational perspective of hiring professionals, college name changes are associated with an increase in candidate performance on an employer-administered aptitude test. Specifically, in this data we see that applicants who enrolled in a name-changing college after it changed its name have measurably higher scores on the civil service exam than applicants who graduate from the same college before it changed its name. While not causal, this suggests that recruiters, particularly those who administer aptitude tests, may observe an increase in the quality of graduates at name-changing colleges after the change. We present further analysis of these data in Appendix G.

Second, we analyze data from an online survey of 87 HR professionals located via the professional networks of our research team. The survey consisted of both multiple choice and free response questions. The survey asked these professionals about their awareness of the phenomenon of college name changes and their opinion of it. Nearly all (97%) reported awareness of the phenomenon, and 60% believed these changes would result in the college attracting and producing better students. Nearly all also believed that college name changes were likely to benefit students on the job market. Consistent with our findings in the previous section, several respondents indicated that, for relatively lower-paying jobs, applicants listing a college's new name might be overqualified and therefore less attractive to the employer than those listing the old name.⁵⁵ We also find that respondents whose main responsibility was hiring candidates in administration were either indifferent between applicants listing a college's old name or its new name, or preferred ap-

⁵⁵The reason for this, they explained, was that the applicant might be overqualified and thus at greater risk of low performance or even quitting, necessitating another costly search.

plicants listing the old name. Those hiring primarily in programming, on the other hand, reported strict preference for candidates listing the new name. In Appendix H, we analyze these data further.

5 Conclusion

Using administrative and experimental data from China, we study how college name changes affect college choice and the labor market performance of recent college graduates. We show that these name changes generate real increases in the quality of the college, as measured by the aptitude of the students it recruits. These increases accrue even when the new, more appealing name contains no other information about fundamental traits of the institution, as well as when the new name contains false information. These effects are also larger among students with less baseline information about the name-changing college. Analysis of scraped text data from online discussion boards in China reveals that these effects are likely to flow through two parallel mechanisms: one, students with asymmetric information responding to the signal sent by the name, even in cases where this signal sends false information; and two, students rationally responding to a likely increase in student quality partially caused by the first channel.

We use three sets of data – a large resume audit study, administrative data from China’s civil service, and a survey of employers – to assess the impacts of these changes on labor market performance of graduates from name-changing colleges. We find that college name changes have no substantial overall impact on graduates’ early labor market performance, though this comprises heterogeneity by job type: we observe a significant negative impact in low-pay, low-status jobs where candidates listing the new college name may appear overqualified. In other, higher-pay and higher-status jobs, we find positive but very small and statistically insignificant impacts. These latter estimates are also precise: the confidence intervals around these estimates rule out a wide range of effects of even modest magnitude. Analysis of administrative and survey data from employers show that professionals responsible for hiring recent college graduates are aware of the fact that name-changing colleges attract students with higher entrance scores, see observable differences in performance on recruitment exams between applicants graduating from these colleges before versus after the name change, and claim to respond to name changes in their recruitment behavior.

We study only a few key steps in a complex process. On the student side, our analyses show how college name changes affect the aptitude of recruited students, and common perceptions of college name changes expressed by students online. Many factors may underlie these patterns, such as strategic college choice based on probability of admission and selectivity of school, future expectations of the school's prestige, and anticipated labor market returns. On the employer side, our analyses show whether and when new college names receive a premium in the early stages of the labor market, and the beliefs and perceptions of employers regarding the likely impacts of college name changes on the traits of graduates from name-changing colleges. Here too, many factors may underlie this phenomenon, such as whether college names – for example, geographic names – may help with coordination between employers and applicants, or whether features of college names may convey other information to employers about graduates that we do not capture. We leave the study of these and other mechanisms to future work.

As a whole, our study highlights a key feature of markets with imperfect information. Even in “high stakes” markets such as those we study, participants often send signals designed to change other participants' beliefs, some of which even send false information. We show that these signals can generate real, self-fulfilling processes in these – and likely other – important markets.

References

- Acton, Riley K**, “Is a name change a game change? The impact of college-to-university conversions,” *Economics of Education Review*, 2022, 88, 102240.
- Agan, Amanda and Sonja Starr**, “Ban the box, criminal records, and racial discrimination: A field experiment,” *Quarterly Journal of Economics*, 2018, 133 (1), 191–235.
- Akerlof, George A**, “The market for “lemons”: Quality uncertainty and the market mechanism,” *Quarterly Journal of Economics*, 1970, 84 (3), 488–500.
- Alter, Molly and Randall Reback**, “True for your school? How changing reputations alter demand for selective US colleges,” *Educational Evaluation and Policy Analysis*, 2014, 36 (3), 346–370.
- Altonji, Joseph G**, “The demand for and return to education when education outcomes are uncer-

- tain,” *Journal of Labor Economics*, 1993, 11 (1, Part 1), 48–83.
- Andrabi, Tahir, Jishnu Das, and Asim Ijaz Khwaja**, “Report cards: The impact of providing school and child test scores on educational markets,” *American Economic Review*, 2017, 107 (6), 1535–1563.
- Arcidiacono, Peter, Patrick Bayer, and Aurel Hizmo**, “Beyond signaling and human capital: Education and the revelation of ability,” *American Economic Journal: Applied Economics*, 2010, 2 (4), 76–104.
- Associated Press**, “Name Game: Colleges Rebrand to Attract More Students,” July 2015. URL: <https://www.nbcnews.com/feature/freshman-year/whats-name-colleges-rebrand-attract-more-students-n391221>, accessed October 13, 2020.
- Bagwell, Kyle and Garey Ramey**, “Advertising and coordination,” *Review of Economic Studies*, 1994, 61 (1), 153–171.
- **and** —, “Coordination economies, advertising, and search behavior in retail markets,” *American Economic Review*, 1994, 84 (3), 498–517.
- Belenzon, Sharon, Aaron K Chatterji, and Brendan Daley**, “Eponymous entrepreneurs,” *American Economic Review*, 2017, 107 (6), 1638–55.
- Belman, Felice**, “Same schools, new name,” *Boston Globe*, August 9 2017.
- Bergman, Peter**, “Parent-child information frictions and human capital investment: Evidence from a field experiment,” *Journal of Political Economy*, 2021, 129 (1), 286–322.
- Bertrand, Marianne and Sendhil Mullainathan**, “Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination,” *American Economic Review*, 2004, 94 (4), 991–1013.
- Bo, Shiyu, Jing Liu, Ji-Liang Shiu, Yan Song, and Sen Zhou**, “Admission mechanisms and the mismatch between colleges and students: Evidence from a large administrative dataset from China,” *Economics of Education Review*, 2019, 68, 27–37.
- Bolton, Patrick, Mathias Dewatripont et al.**, *Contract Theory*, MIT press, 2005.
- Borusyak, Kirill, Xavier Jaravel, and Jann Spiess**, “Revisiting event study designs: Robust and

efficient estimation,” *arXiv preprint arXiv:2108.12419*, 2021.

Callaway, Brantly and Pedro HC Sant’Anna, “Difference-in-differences with multiple time periods,” *Working Paper*, 2019.

Card, David, “Estimating the return to schooling: Progress on some persistent econometric problems,” *Econometrica*, 2001, 69 (5), 1127–1160.

Carey, Colleen M, Sarah Miller, and Laura R Wherry, “The impact of insurance expansions on the already insured: the Affordable Care Act and Medicare,” *American Economic Journal: Applied Economics*, 2020, 12 (4), 288–318.

Chen, Mingyu, “The value of US college education in global labor markets: Experimental evidence from China,” Technical Report, Princeton University, Department of Economics, Industrial Relations Section. 2019.

Chen, Yan and Onur Kesten, “Chinese college admissions and school choice reforms: A theoretical analysis,” *Journal of Political Economy*, 2017, 125 (1), 99–139.

—, **Ming Jiang, and Onur Kesten**, “An empirical evaluation of Chinese college admissions reforms through a natural experiment,” *Proceedings of the National Academy of Sciences*, 2020, 117 (50), 31696–31705.

Clark, Kim, “Colleges play the name game,” *US News and World Report*, September 17 2009.

Clinton, Kirsten, “What’s in a name? The signaling value of university education,” *Working Paper*, 2020.

Corcoran, Sean and Henry M Levin, “School choice and competition in the New York City schools,” in “Education Reform in New York City: An Ambitious Change in the Nation’s Most Complex School System,” Harvard University Press, 2011.

Corcoran, Sean P, Jennifer L Jennings, Sarah R Cohodes, and Carolyn Sattin-Bajaj, “Leveling the playing field for high school choice: Results from a field experiment of informational interventions,” *NBER Working Paper 24471*, 2018.

Darolia, Rajeev, Cory Koedel, Paco Martorell, Katie Wilson, and Francisco Perez-Arce, “Do employers prefer workers who attend for-profit colleges? Evidence from a field experiment,”

- Journal of Policy Analysis and Management*, 2015, 34 (4), 881–903.
- de Chaisemartin, Clement and Xavier d’Haultfoeuille**, “Two-way fixed effects estimators with heterogeneous treatment effects,” *American Economic Review*, 2020, 110 (9), 2964–96.
- Deming, David J, Claudia Goldin, and Lawrence F Katz**, “The for-profit postsecondary school sector: Nimble critters or agile predators?,” *Journal of Economic Perspectives*, 2012, 26 (1), 139–64.
- , **Noam Yuchtman, Amira Abulafi, Claudia Goldin, and Lawrence F Katz**, “The value of postsecondary credentials in the labor market: An experimental study,” *American Economic Review*, 2016, 106 (3), 778–806.
- Dillon, Eleanor Wiske and Jeffrey Andrew Smith**, “Determinants of the match between student ability and college quality,” *Journal of Labor Economics*, 2017, 35 (1), 45–66.
- Dizon-Ross, Rebecca**, “Parents’ beliefs about their children’s academic ability: Implications for educational investments,” *American Economic Review*, 2019, 109 (8), 2728–65.
- Fang, Hanming, Chang Liu, and Li-An Zhou**, “Window dressing in the public sector: A case study of China’s compulsory education promotion program,” *NBER Working Paper Number 27628*, 2020.
- Finder, Alan**, “To woo students, colleges choose names that sell,” *New York Times*, August 11 2005.
- Goodman-Bacon, Andrew**, “Difference-in-differences with variation in treatment timing,” *Journal of Econometrics*, 2021, 225 (2), 254–277.
- Hastings, Justine S and Jeffrey M Weinstein**, “Information, school choice, and academic achievement: Evidence from two experiments,” *Quarterly Journal of Economics*, 2008, 123 (4), 1373–1414.
- Hoxby, Caroline and Sarah Turner**, “Expanding college opportunities for high-achieving, low income students,” *Stanford Institute for Economic Policy Research Discussion Paper*, 2013.
- Hoxby, Caroline M**, *The Economics of School Choice*, University of Chicago Press, 2007.
- , “The changing selectivity of American colleges,” *Journal of Economic Perspectives*, 2009, 23

- (4), 95–118.
- **and Sarah Turner**, “What high-achieving low-income students know about college,” *American Economic Review*, 2015, 105 (5), 514–17.
- Jensen, Robert**, “The (perceived) returns to education and the demand for schooling,” *Quarterly Journal of Economics*, 2010, 125 (2), 515–548.
- Jia, Ruixue and Hongbin Li**, “Just above the exam cutoff score: Elite college admission and wages in China,” *Journal of Public Economics*, 2021, 196 (104371).
- Koszegi, Botond**, “Behavioral contract theory,” *Journal of Economic Literature*, December 2014, 52 (4), 1075–1118.
- Kuhn, Peter and Kailing Shen**, “Gender discrimination in job ads: Evidence from china,” *Quarterly Journal of Economics*, 2013, 128 (1), 287–336.
- , – , **and Shuo Zhang**, “Gender-targeted job ads in the recruitment process: Evidence from china,” *NBER Working Paper 25365*, 2018.
- Li, Hongbin and Li-An Zhou**, “Political turnover and economic performance: the incentive role of personnel control in China,” *Journal of Public Economics*, 2005, 89 (9-10), 1743–1762.
- , **Lei Li, Binzhen Wu, and Yanyan Xiong**, “The end of cheap Chinese labor,” *Journal of Economic Perspectives*, 2012, 26 (4), 57–74.
- Liu, Elaine and Shu Zhang**, “A Meta-Analysis Of The Estimates Of Returns To Schooling In China,” *Working Paper*, 2013.
- Loewenstein, George, Ted O’Donoghue, and Matthew Rabin**, “Projection bias in predicting future utility,” *Quarterly Journal of Economics*, 2003, 118 (4), 1209–1248.
- Loyalka, Prashant, Y. Qu, Binzhen Wu, and X.Y. Ye**, “How college choices disadvantage disadvantaged students under centralized college admissions systems,” *Working Paper*, 2021.
- MacLeod, W Bentley and Miguel Urquiola**, “Reputation and school competition,” *American Economic Review*, 2015, 105 (11), 3471–88.
- **and** – , “Is education consumption or investment? Implications for school competition,” *Annual Review of Economics*, 2019, 11, 563–589.

- , **Evan Riehl, Juan E Saavedra, and Miguel Urquiola**, “The big sort: College reputation and labor market outcomes,” *American Economic Journal: Applied Economics*, 2017, 9 (3), 223–61.
- Mayzlin, Dina and Jiwoong Shin**, “Uninformative advertising as an invitation to search,” *Marketing Science*, 2011, 30 (4), 666–685.
- McDevitt, Ryan C**, ““A” business by any other name: firm name choice as a signal of firm quality,” *Journal of Political Economy*, 2014, 122 (4), 909–944.
- Milgrom, Paul and John Roberts**, “Price and advertising signals of product quality,” *Journal of Political Economy*, 1986, 94 (4), 796–821.
- Ministry of Human Resources and Social Security of the People’s Republic of China**, “National human resources service sector development current conditions - 2018 human resources service statistics update (in Chinese, woguo renli ziyuan fuwuye fazhan zaishang xin taijie - 2018 nian renli ziyuan fuwuye tongji qingquang,” Technical Report 2019. Accessed March 28, 2020; url [http : //www.mohrss.gov.cn/SYrlzyhshbzb/dongtaixinwen/buneyaowen/201905/t20190524_318428.html](http://www.mohrss.gov.cn/SYrlzyhshbzb/dongtaixinwen/buneyaowen/201905/t20190524_318428.html).
- , “Statistical communique on the development of human resources and social security in 2018; in Chinese: 2018 niandu renli ziyuan he shehui baozhang shiye fazhan tongji gongbao,” Technical Report 2019. Accessed March 28, 2020; url [http : //www.mohrss.gov.cn/SYrlzyhshbzb/zwgk/szrs/tjgb/201906/t20190611_320429.html](http://www.mohrss.gov.cn/SYrlzyhshbzb/zwgk/szrs/tjgb/201906/t20190611_320429.html).
- Mulhern, Christine**, “Changing college choices with personalized admissions information at scale: Evidence on Naviance,” *Journal of Labor Economics*, 2021, 39 (1), 219–262.
- Newlon, Cara**, “The college amenities arms race,” *Forbes*, July 31 2014.
- Owston, James M**, “Survival of the fittest? The re-branding of West Virginia higher education,” *International Journal of Educational Advancement*, 2009, 9 (3), 126–146.
- Platt, R Eric, Steven R Chesnut, Melandie McGee, and Xiaonan Song**, “Changing names, merging colleges: Investigating the history of higher education adaptation,” *American Educational History Journal*, 2017, 44 (1/2), 49–67.
- Pope, Devin G and Jaren C Pope**, “The impact of college sports success on the quantity and

- quality of student applications,” *Southern Economic Journal*, 2009, 75 (3), 750–780.
- Rubinstein, Yona and Dror Brenner**, “Pride and prejudice: Using ethnic-sounding names and inter-ethnic marriages to identify labour market discrimination,” *Review of Economic Studies*, 2014, 81 (1), 389–425.
- Russell, Lauren**, “Price Effects of Nonprofit College and University Mergers,” *Review of Economics and Statistics*, 2021, 103 (1), 88–101.
- Sekhri, Sheetal**, “Prestige matters: Wage premium and value addition in elite colleges,” *American Economic Journal: Applied Economics*, 2020, 12 (3), 207–225.
- Shi, Yang, Ruiming Liu, and Yankun Kang**, “Does a name change attract better students? Evidence from Chinese universities,” *China Economic Review*, 2020, 60, 101395.
- Spence, Michael**, “Job market signaling,” *Quarterly Journal of Economics*, 1973, 87 (3), 355–374.
- Stiglitz, Joseph E.**, “The theory of “screening,” education, and the distribution of income,” *American Economic Review*, 1975, 65 (3), 283–300.
- Sun, Liyang and Sarah Abraham**, “Estimating dynamic treatment effects in event studies with heterogeneous treatment effects,” *Journal of Econometrics*, 2021, 225 (2), 175–199.
- Tadelis, Steven**, “What’s in a name? Reputation as a tradeable asset,” *American Economic Review*, 1999, 89 (3), 548–563.
- Troop, Don**, “What’s in a Name? Letters, and Lots of’Em,” *Chronicle of Higher Education*, November 2008.
- Tversky, Amos and Daniel Kahneman**, “Judgment under uncertainty: Heuristics and biases,” *Science*, 1974, 185 (4157), 1124–1131.
- Weiss, Andrew**, “Human capital vs. signalling explanations of wages,” *Journal of Economic Perspectives*, 1995, 9 (4), 133–154.
- Winter, Greg**, “Jacuzzi U.? A battle of perks to lure students,” *New York Times*, October 5 2003.
- Wong, Alia**, “What’s the difference between a college and a university?,” *The Atlantic*, November 19 2019.
- Yaisawarng, Suthathip and Ying Chu Ng**, “The impact of higher education reform on research

performance of Chinese universities,” *China Economic Review*, 2014, 31, 94–105.

Yu, Kai, Andrea Lynn Stith, Li Liu, and Huizhong Chen, *Tertiary education at a glance: China*, Springer Science & Business Media, 2012.

Zhang, Yu, *National college entrance exam in China: Perspectives on education quality and equity*, Springer Briefs in Education, 2016.

Zimmerman, Seth, “The returns to college admission for academically marginal students,” *Journal of Labor Economics*, 2014, 32 (4), 711–754.

Table 1: Types of name change

| <i>Type</i> | <i>Description</i> | <i>Name</i> | <i>Example</i> | <i>Resource requirements</i> | <i>Initiated by college</i> |
|-------------|--|-------------|--|--------------------------------|-----------------------------|
| 1 | Institute/college to university | Old New | Shanghai College of Electric Power Shanghai University of Electric Power | Yes | Yes |
| 2 | Change in geographic scope | Old New | Xuzhou Normal University Jiangsu Normal University | No | Yes |
| 3 | Change in industrial focus | Old New | Zhejiang College of Education Zhejiang College of International Studies | No | Yes |
| 4 | Changes to more than one aspect | Old New | Zhuzhou College of Technology Hunan University of Technology | Only if change includes type 1 | Yes |
| 5a | Private college, parent college changes its name | Old New | Hubei Normal College – Wenli College Hubei Normal University – Wenli College | No | No |
| 5b | Private college forced to drop parent college name | Old New | Anhui Polytechnic University – College of Mechanical & Electrical Engineering Anhui College of Information Technology | Yes | No |

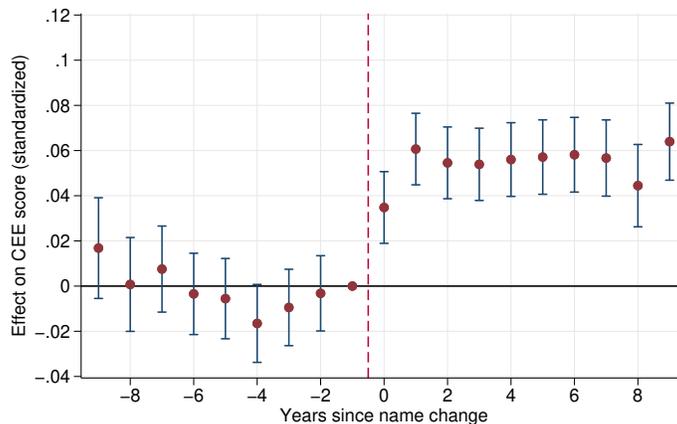
Note: this table classifies the different types of name changes that occurred among Chinese colleges over the period 1980-2019, and provides examples of each type.

Table 2: Effects of college name changes on average CEE scores of enrolled students

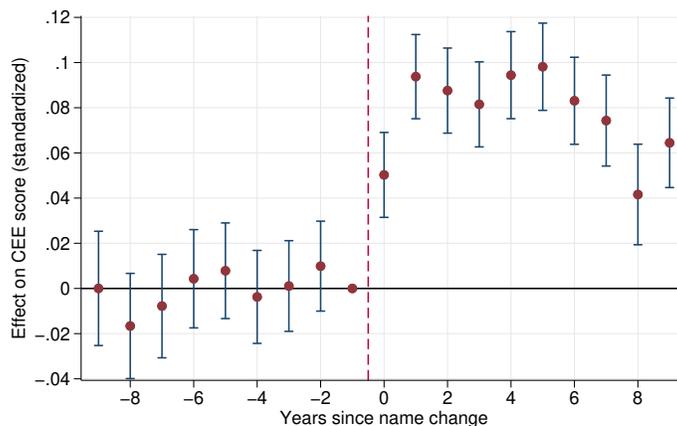
| | (1) | (2) |
|---|---------------------|-----------------------|
| | All name changes | College to university |
| Effect on average CEE score (in SD units) | 0.057*** (0.003) | 0.077*** (0.004) |
| Adjusted R-squared | 0.905 | 0.905 |
| Number of observations | 418,441 | 418,441 |

Note: this table shows our estimates of how college name changes affect the mean CEE scores of students enrolling in name changing colleges in a given year, as compared with institutions who did not change their names. The row entitled “Effect on average CEE score (in SD units)” reports our estimate of β_1 in Equation 1 for the treated group named in the column headings. The removal of the $NewName_{ct}$ variable changes the goodness of fit by 0.001 in both columns. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Event study - effects of college name changes on average CEE scores over time



Panel A: All name changes



Panel B: College to university changes only

Note: this figure shows the coefficient estimates and corresponding confidence intervals from estimating Equation 2. In Panel A, we show this for all name changing colleges (corresponding to column 1 of Table 2). In Panel B, we show this for colleges whose name changes include a change from college to university (corresponding to column 2 of that table). In Figure A.3, we show an analogue to this figure excluding data from colleges which did not change their names. This figure includes all but the single most extreme lead and lag (10 years to and from change, respectively); in Figure A.5 we show the analogue figure with these most extreme lags included.

Table 3: Effects of alluring but misinformative name changes

| <i>Panel A: Name change includes alluring but misleading geographic information</i> | | |
|--|--|---------------------------------|
| | (1) | (2) |
| | New name is alluring but misleading | All other name changes |
| Effect on average CEE score (in SD units) | 0.084*** (0.007) | 0.048*** (0.004) |
| Adjusted R-squared | 0.905 | 0.905 |
| Number of observations | 418,441 | 418,441 |
| <i>Panel B: Private college name changes where signal indicates incorrect quality change</i> | | |
| | (1) | (2) |
| | Uses parent college's new name | Drops link to parent college |
| Effect on average CEE score (in SD units) | 0.088*** (0.008) | -0.014* (0.008) |
| Adjusted R-squared | 0.905 | 0.905 |
| Number of observations | 418,441 | 418,441 |

Note: this table shows our estimates of β_1 from Equation 1 for name changes which are alluring, but contain either false or no information about the college's fundamental traits. In Panel A we show estimates for name changes which do and do not convey misinformative signals about the location of the college, as indicated in the column heading. In Panel B we show estimates for name changes among private colleges, first for those who benefit from a name change occurring at (and initiated by) their "parent" college, and then for private colleges forced to drop the link to the parent college in their name. Column headings indicate the type of name change for which the effect is estimated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Heterogeneity in effects by information held about the college

| <i>Panel A: All name changes vs. college-to-university changes</i> | | | | |
|--|-------------------------------------|------------------------------|-------------------------------------|------------------------------|
| | <i>Out-of-province applicants</i> | | <i>Within-province applicants</i> | |
| | (1) | (2) | (3) | (4) |
| | All name changes | College to university | All name changes | College to university |
| Effect on average CEE score (in SD units) | 0.059*** (0.004) | 0.080*** (0.005) | 0.041*** (0.015) | 0.043*** (0.018) |
| Adjusted R-squared | 0.908 | 0.908 | 0.915 | 0.915 |
| Number of observations | 393,292 | 393,292 | 25,139 | 25,139 |
| <i>Panel B: Name change includes alluring but misleading geographic information</i> | | | | |
| | <i>Out-of-province applicants</i> | | <i>Within-province applicants</i> | |
| | (1) | (2) | (3) | (4) |
| | New name is alluring but misleading | All other name changes | New name is alluring but misleading | All other name changes |
| Effect on average CEE score (in SD units) | 0.083*** (0.008) | 0.051*** (0.004) | 0.032 (0.028) | 0.041*** (0.016) |
| Adjusted R-squared | 0.908 | 0.908 | 0.915 | 0.915 |
| Number of observations | 393,292 | 393,292 | 25,139 | 25,139 |
| <i>Panel C: Private college name changes where signal indicates incorrect quality change</i> | | | | |
| | <i>Out-of-province applicants</i> | | <i>Within-province applicants</i> | |
| | (1) | (2) | (3) | (4) |
| | Uses parent college's new name | Drops link to parent college | Uses parent college's new name | Drops link to parent college |
| Effect on average CEE score (in SD units) | 0.094*** (0.008) | -0.015* (0.008) | 0.050 (0.034) | 0.030 (0.035) |
| Adjusted R-squared | 0.908 | 0.908 | 0.915 | 0.915 |
| Number of observations | 393,292 | 393,292 | 25,139 | 25,139 |

Note: this table shows estimates of β_1 in Equation 1, mirroring results in Tables 2 and 3, for applicants from outside of the province in which the college is located, and those from within the province, respectively, as indicated in the column super-headings. Panel A shows these results overall; Panels B and C show them for the types of name change studied in Panels A and B of Table 3, respectively. In the column headings we indicate the type of name change for which the effect is estimated. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Callback rates by resume type and job type

| | (1) | (2) | (3) | (4) | (5) | (6) |
|--|---------------------------|---------------------------|---------------------------|--------------------------|--------------------------|---------------------------|
| | Old name callback rate | New name callback rate | Difference (new - old) | Difference in % terms | P-value of difference | Number of observations |
| All resumes | 0.1379 | 0.1347 | -0.0033 | -2.4% | 0.573 | 14,152 |
| Five years of experience | 0.1264 | 0.1362 | 0.0098 | 7.7% | 0.234 | 6,740 |
| Two years of experience | 0.1484 | 0.1333 | -0.0151 | -10.2% | 0.062 | 7,412 |
| Programming jobs | 0.1255 | 0.1338 | 0.0083 | 6.6% | 0.293 | 7,206 |
| Administration jobs | 0.1509 | 0.1356 | -0.0153 | -10.1% | 0.070 | 6,946 |
| Job and college in same province | 0.1436 | 0.1353 | -0.0083 | -5.8% | 0.317 | 6,990 |
| Job and college in different provinces | 0.1324 | 0.1340 | 0.0017 | 1.3% | 0.835 | 7,162 |

Note: this table shows our primary outcome for the resume audit study, a comparison of the callback rates received by resumes listing a college's old name and those received by resumes listing its new name. We present the mean callback rate for each job type, defined in the leftmost column, by resume type, with those listing the old name in column (1), and those listing the new name in column (2). We also show their difference, this as a proportion of the old name callback rate, and the p-value from a t-test of their equality. Since there are an equal number of old name and new name resumes in each row, the overall callback rate for a given row is the mean of columns (1) and (2).

Table 6: Heterogeneity in new name callback premium

| | <i>Jobs in administration</i> | | <i>Jobs in programming</i> | |
|---|-----------------------------------|------------------------------------|-----------------------------------|------------------------------------|
| | (1) Two years of experience | (2) Five years of experience | (3) Two years of experience | (4) Five years of experience |
| α : New name callback rate minus old name callback rate | -0.033*** | 0.007 | 0.005 | 0.012 |
| α as percent of old name callback rate | -15.5% | 9.8% | 5.8% | 7.0% |
| P-value of test: $\alpha = 0$ | [p=0.010] | [p=0.455] | [p=0.620] | [p=0.342] |
| Old name callback rate | 0.210 | 0.074 | 0.079 | 0.169 |
| Number of observations | 3,930 | 3,016 | 3,482 | 3,724 |

Notes: this table shows the parameter α , defined as {[new name callback rate] - [old name callback rate]}, for the job type indicated in the column heading. We also show α as a percentage of the old name callback rate for that cell, and a p-value for a t-test of the null that {[new name callback rate] = [old name callback rate]}. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix

Appendix tables and figures

Table A.1: Summary statistics for colleges in college choice data, spanning 2006-2016

| <i>Panel A: Our data</i> | |
|---|----------------------|
| Number of colleges | 1,198 |
| Number of public colleges | 783 |
| Number of private colleges | 415 |
| Number of colleges that changed their names | 244 |
| Mean year of name change | 2011.03 (3.42) |
| Number of students in entering class | 1,828.0 (1,199.9) |
| <i>Panel B: Number of name changes, by type</i> | |
| Changed name from college to university | 109 |
| Name suggests incorrect college location | 45 |
| Private college, parent college changes to more alluring name | 56 |
| Private college, forced to drop parent college name | 60 |

Note: this table shows summary statistics for the colleges in our sample. The standard deviation is shown in parentheses below the mean year of name change, and below the average number of students in the college's entering class. Note that the name change categories in Panel B are not mutually exclusive.

Table A.2: Reporting longer list of coefficients from Table 2

| | (1) | (2) |
|--|----------------------|--------------------------|
| | All name changes | College to university |
| Effect on average CEE score (in SD units) | 0.057*** (0.003) | 0.077*** (0.004) |
| Science track | -0.077*** (0.002) | -0.077*** (0.002) |
| Tier 1 | 1.028*** (0.008) | 1.030*** (0.008) |
| Tier 2 | 0.367*** (0.006) | 0.371*** (0.006) |
| Adjusted R-squared | 0.905 | 0.905 |
| Number of observations | 418,441 | 418,441 |

Note: this table shows additional estimates from the estimation presented in Table 2. It presents results for estimating Equation 1, and here also shows estimates for the science track control (β_2) as well as for tier fixed effects (τ_r ; tier 3 is the excluded category). Because the signs, significance, and relative magnitudes of our estimates for β_2 and τ_r are largely consistent across all of our other analyses of CEE scores, and they do not speak directly to the core research questions of the paper, we do not reproduce other tables with their inclusion in a similar fashion, but these analyses are available on request. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Overall effects of name changes on CEE scores of enrolled students, including fully interacted province–college–track fixed effects

| | (1) | (2) |
|---|---------------------|-----------------------|
| | All name changes | College to university |
| Effect on average CEE score (in SD units) | 0.060*** (0.003) | 0.078*** (0.004) |
| Adjusted R-squared | 0.937 | 0.937 |
| Number of observations | 414,255 | 414,255 |

Note: this table shows results for estimating Equation 1, only replacing the individual fixed effects for college, province, and track with a fully interacted set of college x province x track fixed effects. The row entitled “Effect on average CEE score” reports the results for estimating β_1 in Equation 1 for the group named in the column heading. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Overall effects of name changes on CEE scores of enrolled students, including interactions of name change with track and tier indicators

| | (1) | (2) | (3) | (4) |
|------------------------|----------------------|----------------------|----------------------|----------------------|
| New name | 0.057*** (0.003) | 0.055*** (0.005) | 0.071*** (0.006) | 0.069*** (0.006) |
| Science | -0.077*** (0.002) | -0.077*** (0.002) | -0.077*** (0.002) | -0.077*** (0.002) |
| Tier 1 | 1.028*** (0.008) | 1.028*** (0.008) | 1.033*** (0.009) | 1.033*** (0.009) |
| Tier 2 | 0.367*** (0.006) | 0.367*** (0.006) | 0.370*** (0.006) | 0.370*** (0.006) |
| Science x new name | | 0.002 (0.005) | | 0.003 (0.005) |
| Tier 1 x new name | | | -0.034*** (0.011) | -0.034*** (0.011) |
| Tier 2 x new name | | | -0.019*** (0.007) | -0.019*** (0.007) |
| Adjusted R-squared | 0.905 | 0.905 | 0.905 | 0.905 |
| Number of observations | 418,441 | 418,441 | 418,441 | 418,441 |

Note: this table shows results for replicating column 1 of Table 2, adding in control variables for interactions between the name change variable and the science and tier variables, as indicated by the presence of estimates in each column. The row entitled “New name” reports the results for estimating β_1 in Equation 1, equivalent to that labeled as “Effect on average CEE score” in other tables. We do not present estimates for column 2 of Table 2 here because so few tier 3 colleges changed from college to university over this period. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Analysis of score changes for colleges with initially failed applications

| | (1) | (2) |
|--|---|--|
| | Treatment: year of failed attempt | Treatment: year of successful change |
| Effect on average CEE score (in SD units) | -0.001 (0.010) | 0.030*** (0.013) |
| Adjusted R-squared | 0.905 | 0.905 |
| Number of observations | 417,368 | 418,441 |

Note: this table shows results for estimating Equation 1 using a set of colleges whose application to change their name was initially rejected. Column 1 shows results using the year of the failed change to define treatment status; column 2 shows results using the (later) year of successful name change to define treatment. In these regressions, we use the entire market as the untreated group, i.e., both the group of colleges that did not change their names in this period and other name changing colleges with no failed applications. There are fewer observations in column 1 than in column 2 because in column 1 we drop all the years in which the college had successfully changed its name. The row entitled “Effect on average CEE score” reports the results for estimating β_1 in Equation 1 for the group named in the column heading. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Effect of name changes on CEE scores, using maximum CEE score among admitted students instead of average score

| | (1) | (2) |
|---|---------------------|-----------------------|
| | All name changes | College to university |
| Effect on maximum CEE score (in SD units) | 0.045*** (0.004) | 0.066*** (0.006) |
| Adjusted R-squared | 0.855 | 0.855 |
| Number of observations | 351,699 | 351,699 |

Note: this table shows results analogue to those in Table 2, but using the maximum CEE score at the college–province–year–track level, instead of the average score. The results are similar across the two tables. The row entitled “Effect on average CEE score” reports the results for estimating β_1 in Equation 1 for the group named in the column heading. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Effect of name changes on CEE scores, controlling for quotas

| <i>Panel A: Main effects, sample with enrollment quota data</i> | | |
|---|----------------------------|---------------------------------|
| | (1) All name changes | (2) College to university |
| Effect on average CEE score (in SD units) | 0.067*** (0.008) | 0.067*** (0.009) |
| Adjusted R-squared | 0.904 | 0.904 |
| Number of observations | 147,512 | 147,512 |
| <i>Panel B: Main effects, controlling for enrollment quota</i> | | |
| | (1) All name changes | (2) College to university |
| Effect on average CEE score (in SD units) | 0.067*** (0.008) | 0.067*** (0.009) |
| Adjusted R-squared | 0.904 | 0.904 |
| Number of observations | 147,512 | 147,512 |

Note: this table shows robustness of the results in Table 2 to two alternative specifications. Panel A shows the same specification as in Table 2, but using only colleges in the sample for whom we have data on enrollment quotas. Panel B shows a specification similar to Table 2 and Panel A of this table, but estimated including this quota variable as a control on the right hand side of equation 1. The row entitled “Effect on average CEE score” reports the results for estimating β_1 in Equation 1 for the group named in the column heading. Though the results in Panel A and Panel B appear identical, they are in fact from two separate sets of regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Main effects, using individual-level data

| | (1) | (2) |
|---|-------------------|-----------------------|
| | All name changes | College to university |
| Effect on average CEE score (in points) | 5.868* (3.321) | 9.977*** (3.057) |
| Adjusted R-squared | 0.789 | 0.789 |
| Number of observations | 19,987 | 19,987 |

Note: this table shows analysis of individual-level CEE score data scraped from the websites of Chinese high schools. The estimating equation we use is $Score_{ispct} = \mu_0 + \mu_1 NewName_{ct} + \mu_2 X_i + \mu_3 Private_s + \mu_4 Tier_{ct} + \phi_c + \phi_p + \psi_t + \epsilon_{ispct}$, where $Score_{ispct}$ is the CEE score for student i in high school s from province p who enrolls in college c in year t . X_i is a vector of controls at the student level (gender and track) and $Private_s$ is a dummy variable for whether the student attends a private high school. $Tier_{ct}$ is a control for the tier of the college in that year. The fixed effects ϕ_c , ϕ_p , and ψ_t , are at the college, province, and year level, respectively. The two estimation result columns focus on the group of college name changes as labeled in the column heading, and mirror columns 1 and 2 in Table 2. The outcome variable is in raw CEE points, not standard deviations, because of the nature of the data used in this table. Some Chinese high schools post the CEE scores of their students and the colleges these students attend on their websites. We scraped these data from the websites of 14 high schools, across six different provinces, spanning 20 years of records. While this is a selected sample, we use it to estimate whether the pattern we see of changes in average CEE scores of children going to a given college when it changes its name also hold in individual-level data. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: Heterogeneity in the effects of name changes on CEE scores by college location

| | <i>Colleges in large cities</i> | | <i>Colleges not in large cities</i> | |
|---|---------------------------------|-----------------------|-------------------------------------|-----------------------|
| | (1) | (2) | (3) | (4) |
| | All name changes | College to university | All name changes | College to university |
| Effect on average CEE score (in SD units) | 0.030*** (0.004) | 0.052*** (0.005) | 0.112*** (0.006) | 0.136*** (0.008) |
| Adjusted R-squared | 0.917 | 0.917 | 0.818 | 0.818 |
| Number of observations | 275,819 | 275,819 | 142,622 | 142,622 |

Note: in this table, we compare effects for name changing colleges located in large cities (columns 1 and 2) to those for small and medium-sized cities (columns 3 and 4). The row entitled “Effect on average CEE score” reports the results for estimating β_1 in Equation 1 for the group named in the column heading. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Student beliefs about college name changes

| Message | Quote from discussion board |
|---|---|
| Importance of college names in driving college choice | <i>If Taishan Medical College did not change its name to Shandong First Medical University, I would never apply to this school.</i> |
| Students being misled by new names | <i>Changchun University has several students who were fooled by [its new] name; only at the time of the school opening ceremony when the history of the school was discussed did they find out, and they collapsed/exploded/were furious.</i> |
| Adding a province-level name misled students about the college's location | <i>If you want to talk about a successful name change, you have to mention Jiangsu University! What a thief, am I right? A college with a province-level name, can you guess where it is? Nanjing [the province capital]? No! [Other famous city]? No! [Third famous city]? No! It's in [name of much smaller city]! Hahahahaha. . . can you guess what it's name was before? Zhenjiang Agricultural Machinery College, just hearing it sounds way too "low", I would never have applied. . . it wasn't until I was buying a train ticket did I realize the university wasn't in Nanjing.</i> |
| Out-of-province students being more likely to be misled | <i>As for the effect of name changes, it's just to fool out-of-province students and make more of them want to come here.</i> |
| Gap between the quality implied by the new name and actual quality | <i>The new name is really aggressive, but there's a big gap: the current level of the school's quality is far lower than the level implied by its fancy name.</i> |
| How specific details of name changes can sway college choice | <i>The name change was very successful! The result was it deceived many people! . . . The name change happened in 2006. I applied in 2008 because I saw the name and thought it was super impressive [in Chinese, "baqi"]. I found out that many of my classmates just saw the name "Industrial University" and chose it based on that alone.</i> |
| Geographic name changes likely to mislead out-of-province students | <i>Xuzhou Normal University changing to Jiangsu Normal University. . . is likely to fool many out-of-province students who will think that it's in Nanjing [even though it is not located in Nanjing].</i> |
| Private colleges who lose status by shedding the name of their parent college | <i>Northwestern Polytechnic University - Mingde College changed its name to Xi'an Mingde Technical College: separating itself from Northwestern Polytechnic University [NPU] was good because it doesn't have to give money to NPU, but having lost the name recognition of NPU, it is far less able to compete for students.</i> |

Note: this table provides a series of illustrative anecdotes from the text data we scraped from the website www.zhihu.com and that we analyze in this section.

Table A.11: Colleges used in resume audit study

| <i>Number</i> | <i>Capital city of province</i> | <i>College's old name</i> | <i>College's new name</i> | <i>Year name changed</i> |
|---------------|---------------------------------|---|--|--------------------------|
| 1 | Hangzhou | Zhejiang College of Finance and Economics <i>Zhejiang Caijing Xueyuan</i> | Zhejiang University of Finance and Economics <i>Zhejiang Caijing Daxue</i> | March 2013 |
| 2 | Hangzhou | Zhejiang Oceanic College <i>Zhejiang Haiyang Xueyuan</i> | Zhejiang Oceanic University <i>Zhejiang Haiyang Daxue</i> | January 2016 |
| 3 | Hefei | Anhui College of the Architecture Industry <i>Anhui Jianzhu Gongye Xueyuan</i> | Anhui Architecture University <i>Anhui Jianzhu Daxue</i> | March 2013 |
| 4 | Hefei | Anqing Normal (Teachers) College <i>Anqing Shifan Xueyuan</i> | Anqing Normal University <i>Anqing Shifan Daxue</i> | January 2016 |
| 5 | Shanghai | Shanghai College of Foreign Trade <i>Shanghai Duiwai Maoyi Xueyuan</i> | Shanghai University of Foreign Trade <i>Shanghai Duiwai Maoyi Daxue</i> | March 2013 |
| 6 | Shanghai | Shanghai College of Electrical Studies <i>Shanghai Dianli Xueyuan</i> | Shanghai University of Electrical Studies <i>Shanghai Dianli Daxue</i> | May 2018 |
| 7 | Wuhan | Wuhan College of Industry <i>Wuhan Gongye Xueyuan</i> | Wuhan Light Industry University <i>Wuhan Qingong Xueyuan</i> | March 2013 |
| 8 | Wuhan | Hubei Normal (Teachers) College <i>Hubei Shifan Xueyuan</i> | Hubei Normal University <i>Hubei Shifan Daxue</i> | January 2016 |
| 9 | Xi'an | Xi'an Electrical College <i>Xi'an Dianli Xueyuan</i> | Xi'an Electrical University <i>Xi'an Dianli Daxue</i> | March 2012 |
| 10 | Xi'an | Xi'an College of Finance and Economics <i>Xi'an Caijing Xueyuan</i> | Xi'an University of Finance and Economics <i>Xi'an Caijing Daxue</i> | May 2018 |
| 11 | Zhengzhou | Northeast China Water Resources and Hydropower College <i>Huabei Shuili Shuidian Xueyuan</i> | Northeast China Water Resources and Hydropower University <i>Huabei Shuili Shuidian Daxue</i> | March 2013 |
| 12 | Zhengzhou | Zhengzhou College of Light Industry <i>Zhengzhou Qingongye Xueyuan</i> | Zhengzhou University of Light Industry <i>Zhengzhou Qingongye Daxue</i> | May 2018 |

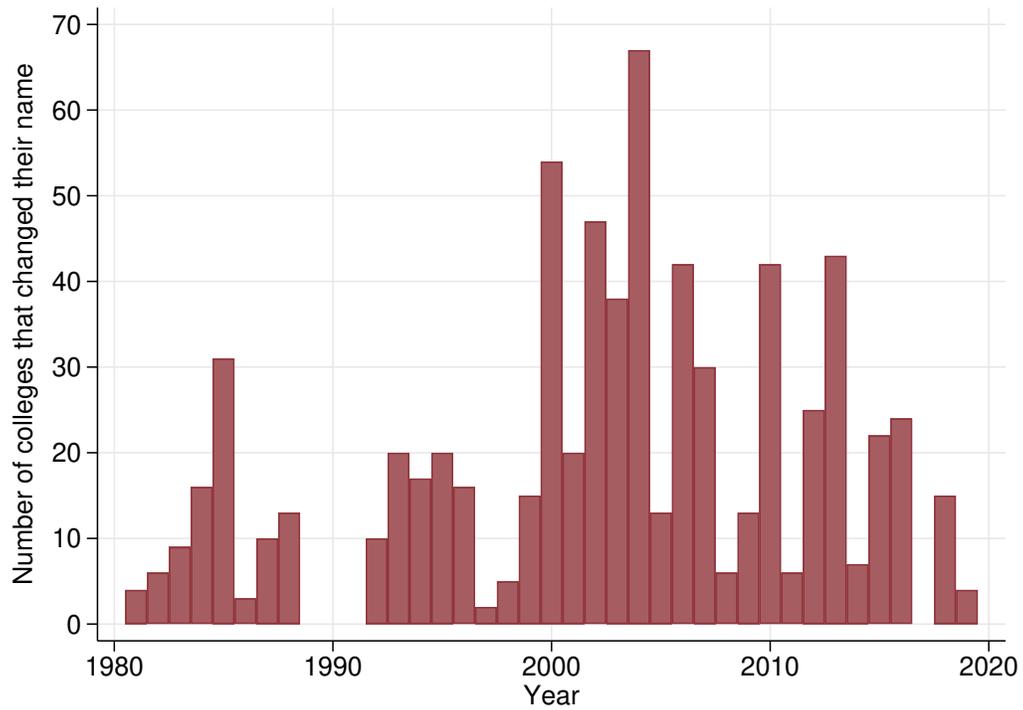
Note: This table lists the old name, new name, and year of name change for colleges used in the resume audit study. For each college, the name in English is given in the first row, and the name in Chinese is given below in italics. The capital city of the province is where the job postings to which we submitted resumes were located.

Table A.12: Heterogeneity in callback rates among jobs in administration requiring two years of experience or less

| Dimension of heterogeneity | Group | (1) Coefficient on new college name | (2) Baseline callback rate | (3) Number of observations |
|----------------------------|-------------------------|---|----------------------------------|----------------------------------|
| <i>Type of firm</i> | Private firm | -0.045*** (0.016) | 0.219 | 2,606 |
| | Publicly traded firm | -0.009 (0.021) | 0.190 | 1,324 |
| <i>Size of firm</i> | Less than 500 employees | -0.035*** (0.015) | 0.221 | 3,046 |
| | 500 employees or more | -0.025 (0.024) | 0.170 | 884 |
| <i>College ranking</i> | Lower ranked | -0.011 (0.018) | 0.202 | 1,862 |
| | Higher ranked | -0.052*** (0.017) | 0.217 | 2,068 |
| <i>Advertised salary</i> | Below median | -0.039*** (0.014) | 0.214 | 3,097 |
| | Above median | -0.011 (0.027) | 0.190 | 815 |
| <i>Credential required</i> | Associate's degree | -0.033** (0.015) | 0.217 | 2,672 |
| | Bachelor's degree | -0.029 (0.024) | 0.184 | 970 |

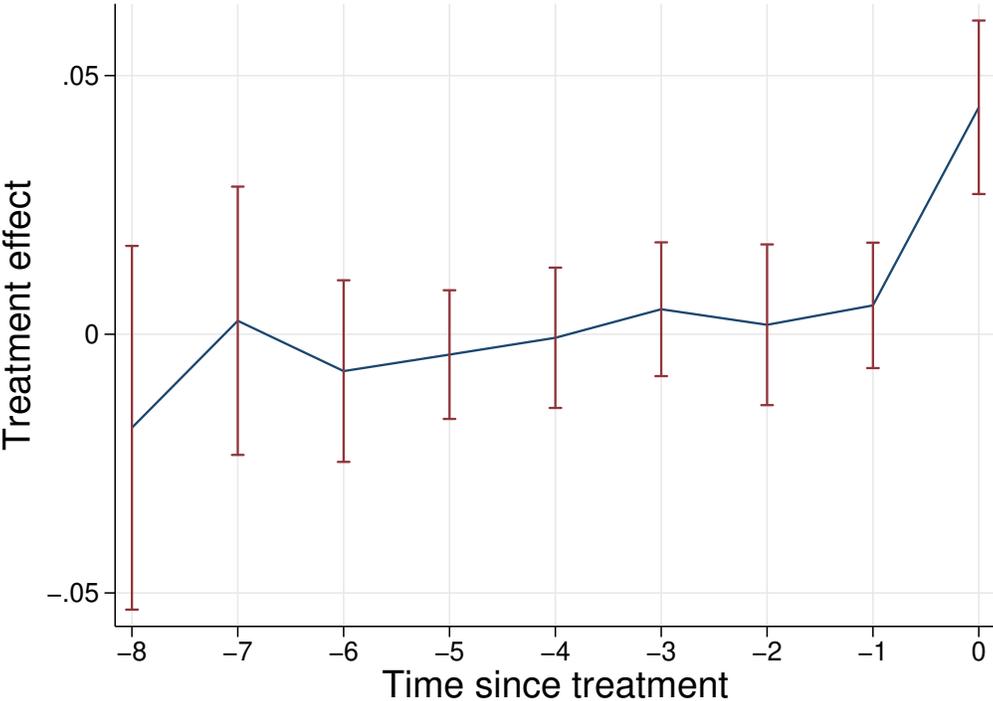
Note: this table shows heterogeneity analysis of callback rates among resumes sent to jobs in administration requiring two years of experience. We report coefficient estimates from regressing the callback rate on an indicator for the resume listing the college's new name, restricting the sample to the criterion described in the second column. Each row represents the results of a separate regression. For advertised salary and credential required, 42 and 408 job postings, respectively, did not list this data and so are not included in those regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1: College name changes in China from 1980-2019



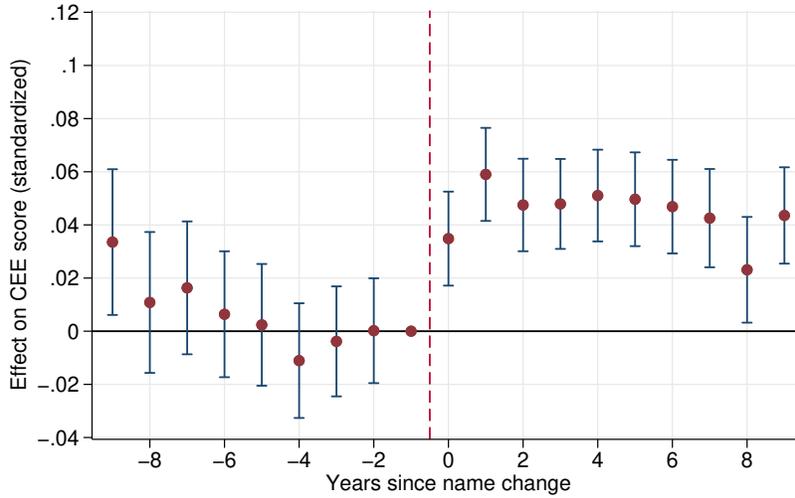
Note: this figure shows the number of colleges which changed their names between 1980 and 2019. We identified the timing of college name changes using Baidu Baike (<https://baike.baidu.com/>), the largest Chinese-language, collaborative, web-based encyclopedia in the world, a website similar to Wikipedia, and confirmed this using information posted on colleges' official websites.

Figure A.2: Parallel trends test from de Chaisemartin and d’Haultfoeuille (2020)

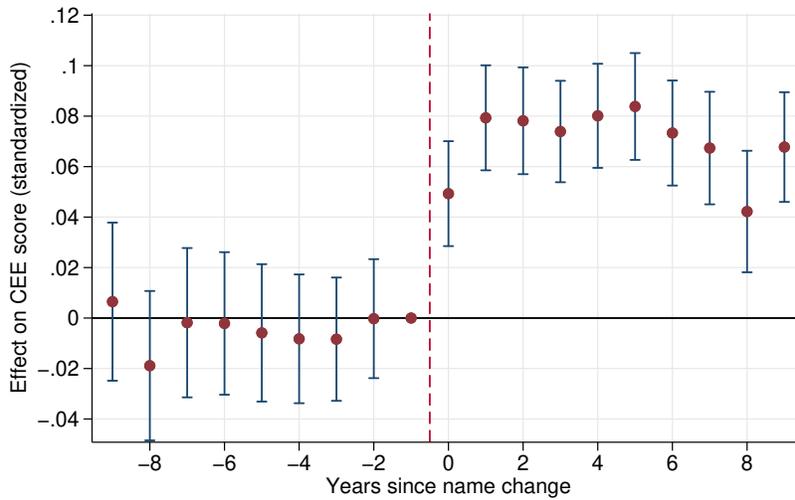


Note: this figure shows placebo estimates from the command *did_multiplt* in de Chaisemartin and d’Haultfoeuille (2020) which offer a further test of the parallel trends assumption. Figure generated using eight placebo periods and 100 replications for the bootstrapped standard errors.

Figure A.3: Event study, name changing colleges only



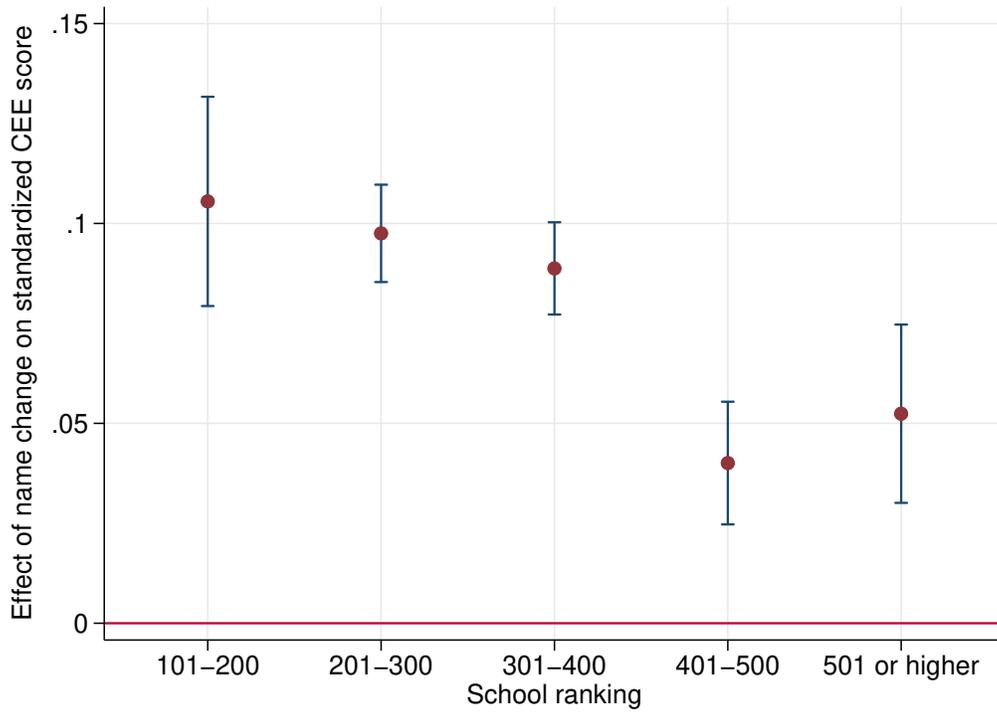
Panel A: All name changes



Panel B: College to university changes only

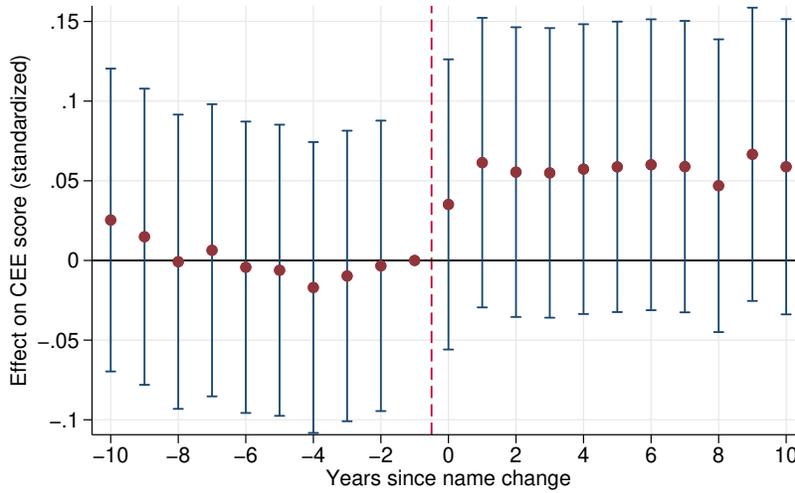
Note: this figure shows an analogue to Figure 1, plotting the coefficient estimates and corresponding confidence intervals from estimating Equation 2 for the treated group in column 2 of Table 2, that is, colleges whose name changes include a change from college to university. In this figure, we exclude data from colleges which did not change their name.

Figure A.4: Heterogeneity in the effect of name changes on CEE scores by baseline college rank

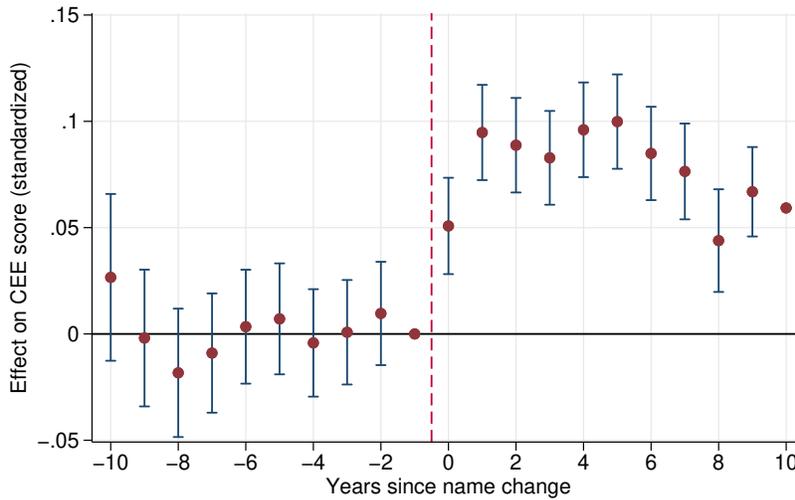


Note: this figure shows estimates of β_1 and corresponding confidence intervals from estimating a version of Equation 1, where the treatment variable is interacted with the five rank tranches shown on the x-axis. The estimating equation is fully saturated; in other words, the equation replaces the one “name change” treatment variable with that variable interacted with an exhaustive set of categorical variables for all possible rankings of treated colleges (no treated colleges are ranked 100 or higher).

Figure A.5: Event study with all possible leads and lags



Panel A: All name changes



Panel B: College to university changes only

Note: this figure reproduces the analysis in Figure 2 while including the two most extreme time lags (-10 years to name change and, separately, +10 years to name change). As in that figure, we show the coefficient estimates and corresponding confidence intervals from estimating Equation 2. In Panel A we show estimates for all name changing colleges (the treated group in column 1 of Table 2). In Panel B we show estimates for colleges whose name changes include a change from college to university (the treated group in column 2 of that table).

Supplementary appendices

A College name changes in the US

In this appendix, we briefly discuss the history of college name changes in the US. While the US and China both have vibrant labor markets, and there is similarly high labor market returns to receipt of a college diploma in the two contexts (Card, 2001; Liu and Zhang, 2013; Zimmerman, 2014), we do not try to make a claim about our estimates' generalizability to the US context. Rather, we use this appendix to highlight that this phenomenon is common even in markets for higher education, such as that in the US, which have been operating for a far longer period of time, and thus a longer period of time during which to establish college reputations.

College name changes have been happening in the US for at least two centuries

The phenomenon we study, colleges changing their names to signal higher quality, is one that occurred commonly among US colleges as early in the nation's history as the first half of the 19th century. Platt et al. (2017). provide an exhaustive study of the history of this process. In Figure 1 of their paper, they document that by 1830, over 50 colleges per decade were changing their names in this way. For example, Queen's College became Rutgers College in 1825, and The College of New Jersey changed its name to Princeton University in 1896.

College name changes are still a feature of the US higher education landscape

Platt et al. (2017) report that there were also hundreds of these changes which took place in the US over the last century. Even today, such name changes continue, particularly at the lower end of the selectivity spectrum (Acton, 2022). In 2015, a newswire article documented that name changes were common among "colleges looking to gain prestige along with more students and precious out-of-state tuition dollars" (Associated Press, 2015). A US News study documented that hundreds of such name changes occurred between 1996 and 2009, though primarily among the least selective institutions (Clark, 2009).

The reasons for these changes in the US are similar to what we document for China

These name changes often involved the switch from the name “college” to the name “university” in order to signal quality: “*Many ‘colleges’ have been relabeled as ‘universities’ to attract larger enrollments via perceived legitimacy as it has been found that the term ‘university’ carries more academic weight with the public than ‘college’*” (Troop, 2008). A more recent report in the Boston Globe claims that these changes often occur with very little else changing about the institution (Belman, 2017). Academic study of this phenomenon corroborates these claims. Owston (2009) uses a mixed-methods approach to study 51 re-branding efforts among colleges in Appalachia between 1996 and 2005, the majority of which were simple replacements of the word “college” with the word “university.” That study found that these changes were made because they were expected to “produce greater prestige and increased enrollment” for the institution (ibid.). For good studies of the US context, see Clinton (2020), who studies the employment effects of name changes on students already enrolled in colleges at the time of the name change, and Acton (2022), who uses an event-study design to study, within-colleges, how name changes affect recruitment at primarily lower-ranked private institutions in the US.

B Name change requirements for the change from college to university

As discussed in Section 2.3, most Chinese college name changes are subject to no explicit requirements from the government. For a college to receive permission to change its name from “college” (*xueyuan*) to “university” (*daxue*), however, the college must meet the following series of requirements set by the Chinese Ministry of Education.

First, the college has to meet requirements for the minimum number of enrolled students. Specifically, the number of full-time students has to be more than 8,000 for the college to change its name to university (*daxue*), while the number needs only to be more than 5,000 for the name “college” (*xueyuan*).

Second, there is a requirement about the minimum number of academic fields offered at the college. Specifically, the number of fields offered should be more than three out of a total of seven officially recognized fields (humanities, social science, science, engineering, agriculture, medicine, and management) for a name change to university, while the institution needs only to offer two or more to hold the college name. In addition, a college needs to have only three or more master’s programs on offer for each academic field, while a university is required to have a total of more than ten offered master programs.

Third, there are requirements about faculty strength. For a college to change its name to university, more than half of faculty members are required to hold at least a master’s degree and at least 20% are required to hold a PhD. For colleges, the proportion of master’s degree-holding faculty members needs only to be 30% or greater, and there is no requirement for PhD degree holders. Furthermore, the number of full professors is required to be more than 100 for a college to change its name to university. For the institution to meet basic college requirements, it only needs to have more than ten.

Fourth, there are teaching requirements. Both colleges and universities have to pass a series of regular teaching evaluations performed by China’s Ministry of Education. For a college to change

its name to university, the institution needs to have received three or more teaching awards at the national level if it is in the first or second tier, or to have received a similar number of awards at the provincial level if it is in the third tier. There were no such requirements for colleges retaining the name “college.”

Fifth, there are requirements about research productivity. For a college to change its name to university, the institution is required to have received a minimum annual amount of research funding (30 million yuan, or roughly US \$3.8 million) in the prior five years. Furthermore, to be called university, the institution needs to have received more than 20 research awards/prizes from award-granting agencies at the provincial or national level.

Sixth and finally, there are overall national requirements about the resources of the institution. The resource requirements pertain to the ratio of various measures of campus offerings – overall acreage of the campus, square footage of buildings, facilities, and library resources – relative to the number of enrolled students. There are no differences in these requirements pertaining to colleges and universities, but because the requirements about the minimum number of students differ between colleges and universities, the resources requirements could impose pressure to “upgrade” for colleges wishing to change their names to university.

Source: Ministry of Education of China. 2006. Requirements on the Qualification of Bachelor-Degree Universities (Pu Tong Ben Ke Xue Xiao She Zhi Zan Xing Gui Ding, in Chinese). Available at <http://old.moe.gov.cn/publicfiles/business/htmlfiles/moes181/201006/88612.html>. Accessed on 2/23/2020.

C Academic resources, scholarly output, and college name changes

Colleges have to apply to the Ministry of Education for approval to change their names. This process involves preparing materials to demonstrate that the college has the necessary level of resources and facilities, as described in Appendix B. We estimate whether college resources or output change when a college changes its name. We focus on the levels of certain college resources related to research support and productivity. We use these to study whether there are other relevant changes concurrent with the name change that might affect instructional quality or the public perception of a university.

In this analysis, we use annual data for 711 of the 783 public colleges in our sample pertaining to the college’s research funding and output, spanning the period from 2007-2016. The main resource-related outcomes we study pertain to the annual scientific output of the university and its faculty strength. These data include the amount of research funding under management by the college, the number of scientific projects at the college funded by the national government, the number of faculty members in the sciences (excluding those in arts, humanities, social sciences, and other non-science departments) working at the college, and the number of academic papers published by faculty there. We gathered these data from the College Science Statistical Yearbooks (*gaodeng xuexiao keji tongji ziliao huibian*) published by the Chinese Ministry of Education.

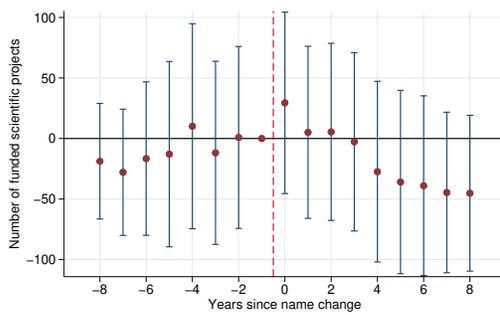
To study this relationship, we estimate a slightly adjusted version of Equation 2,

$$y_{cpstr} = \delta_0 + \sum_{T=-9}^9 \delta_{1\#T} NewName_{Tct} + \theta_{es,c} + \mu_{es,t} + \varepsilon_{cpst} \quad (3)$$

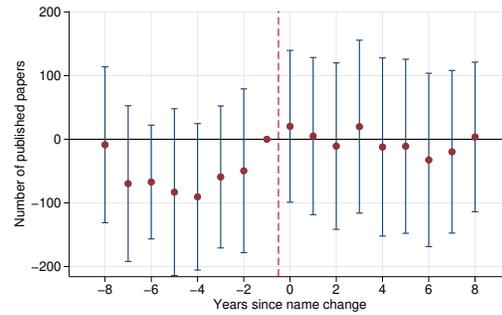
We use outcome variables at the college-by-year level; as a result, we control for only college ($\theta_{es,c}$) and year ($\mu_{es,t}$) fixed effects, with the *es* subscript standing for “event study.” We report our estimates of $\delta_{1\#T}$ in Figure C.1 in a manner parallel to Figure 1. We see that trends in scientific funding and the number of funded projects display no obvious difference before and after the name change. The number of faculty (and, perhaps, the number of published papers) appears to ramp up in the two to three years *before* the name change, and then stays around this level thereafter.

Overall, these patterns are consistent with our interpretation that little about these colleges changes in the year of a name change. To study whether these patterns mask overall changes in norms, in Figure C.2, we also show a version of these event studies using only name-changing colleges (an analogue to Figure A.3). These show that the patterns we reveal are robust to excluding data from other schools which might mask overall changes in the resources these colleges have. In Figure C.3, we present trends in the raw data, in calendar time, for name-changing colleges and the rest of the market, respectively. This also shows a pattern of similarity between trends in the two groups. In Table C.1, we show that our main results are robust to restricting the sample to colleges for whom we have resource data, and to adding controls for these levels of resources.

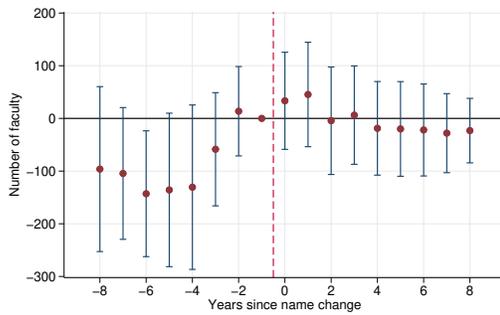
Figure C.1: How resources change with college name changes



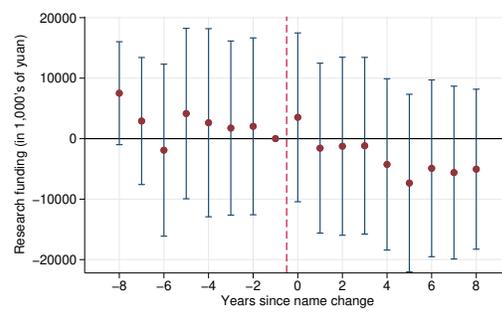
Panel A: Number of scientific projects



Panel B: Number of papers published



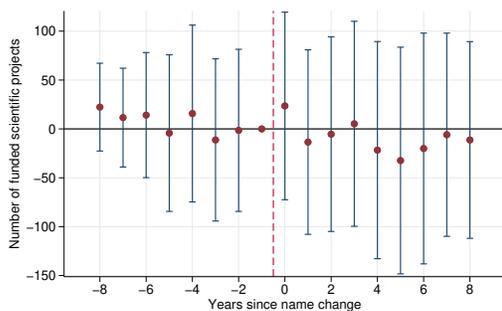
Panel C: Number of faculty



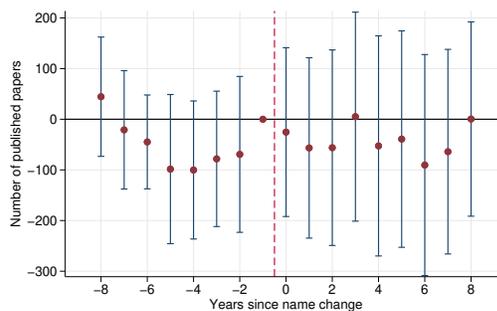
Panel D: Overall research funding

Note: this figure shows event studies, similar to Figure 1, reporting the estimated effect, over time, of college name changes on the college resources described in the panel title and the y-axis of the figure.

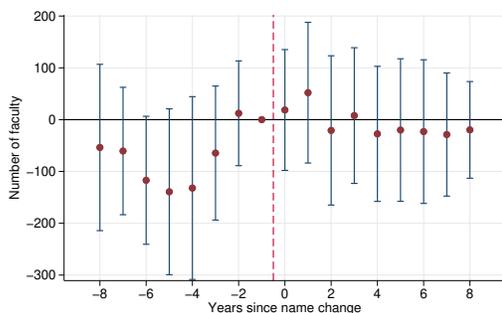
Figure C.2: How resources change with college name changes; name-changing colleges only



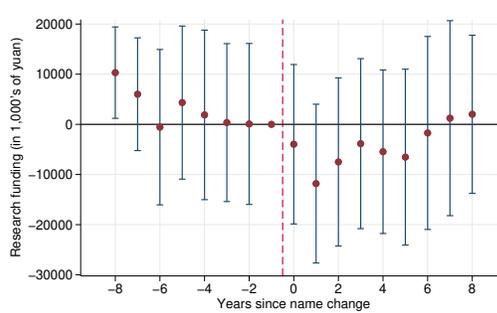
Panel A: Number of scientific projects



Panel B: Number of papers published



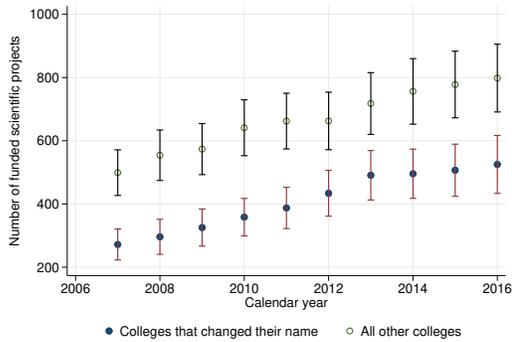
Panel C: Number of faculty



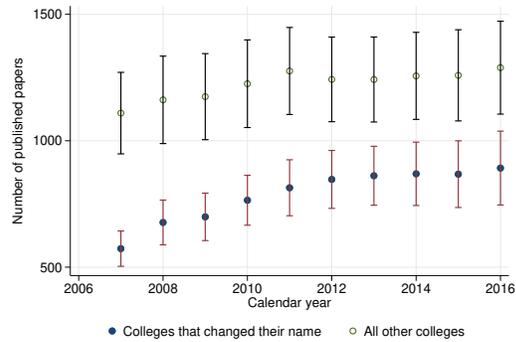
Panel D: Overall research funding

Note: this figure shows an analogue to Figure C.1, restricting our sample to name-changing colleges only (as in Figure A.3). The resource variable is described in the panel title and the y-axis of the figure.

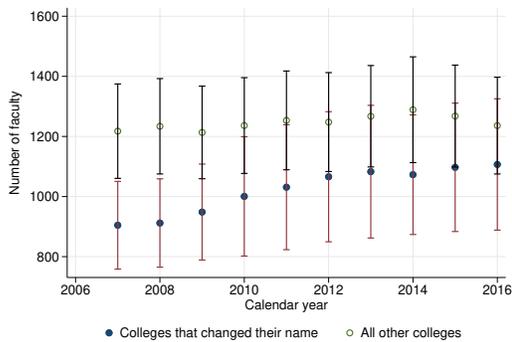
Figure C.3: Raw time trends in college resource levels



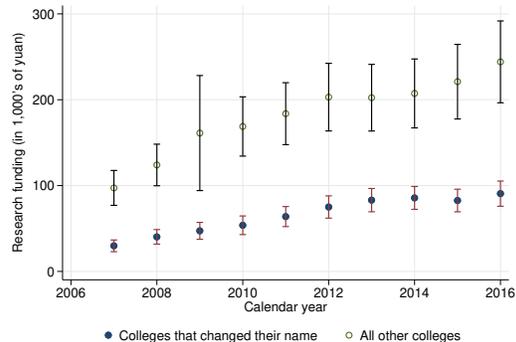
Panel A: Number of scientific projects



Panel B: Number of papers published



Panel C: Number of faculty



Panel D: Overall research funding

Note: this figure shows trends by calendar year in the mean and dispersion (95% confidence interval on the group-specific mean) in the amount of resources and productivity at the colleges in our sample, separately by colleges which did and did not change their names, respectively. The college resource depicted in each figure are described in the panel title and the y-axis of the figure.

Table C.1: Overall effects of name changes on CEE scores of enrolled students, controlling for resources

| <i>Panel A: Main effects, sample with resources data</i> | | |
|--|----------------------------|---------------------------------|
| | (1) All name changes | (2) College to university |
| Effect on average CEE score (in SD units) | 0.083*** (0.004) | 0.092*** (0.005) |
| Adjusted R-squared | 0.887 | 0.887 |
| Number of observations | 269,522 | 269,522 |
| <i>Panel B: Main effects, controlling for resources</i> | | |
| | (1) All name changes | (2) College to university |
| Effect on average CEE score (in SD units) | 0.090*** (0.004) | 0.097*** (0.005) |
| Adjusted R-squared | 0.887 | 0.887 |
| Number of observations | 269,522 | 269,522 |

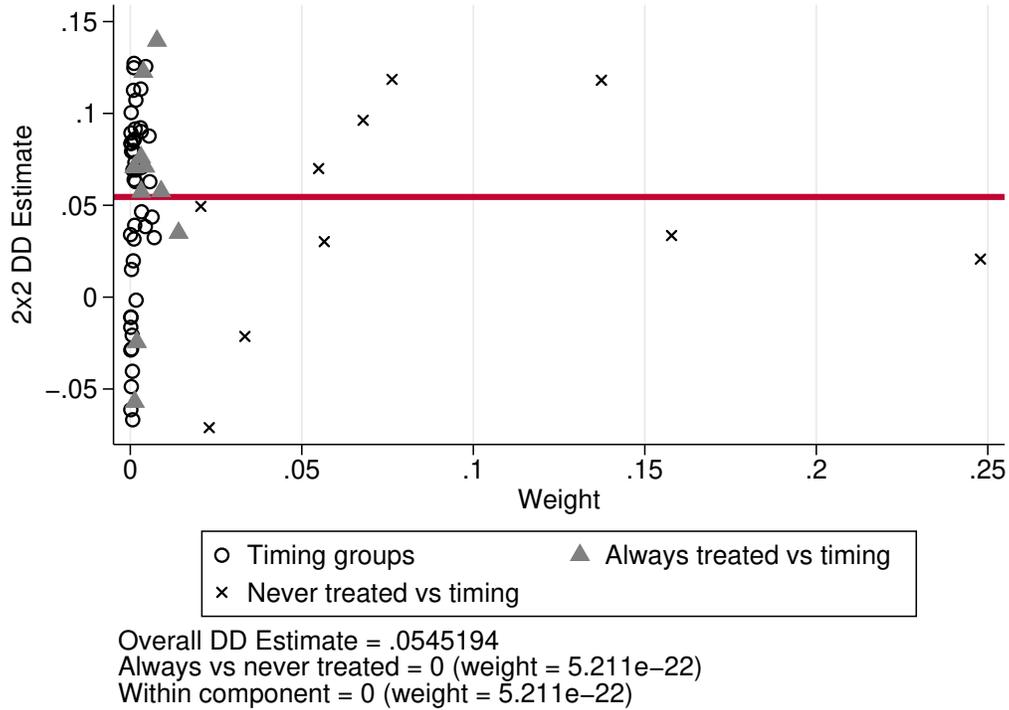
Note: this table shows robustness of the results in Table 2 to two alternative specifications. Panel A shows the same specification as in Table 2, restricting the sample to only those colleges for whom we have the following resources data: annual data on the number of federal projects; the amount of research funding currently under management by the college; the number of papers published; and the number of relevant faculty. Panel B shows a specification similar to Table 2 and Panel A of this table, but estimated including these four “resource” variables as controls on the right hand side of Equation 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Testing for negative weights in ATE estimates

A recent set of studies examines properties of difference-in-differences estimators, bringing attention to the fact that the overall estimand from a difference-in-differences analysis of a policy or experiment with staggered timing of implementation is a weighted average of four types of potential comparison: one, the never treated vs. those treated “early”; two, the never treated vs. those treated “late”; three, those treated early vs. those treated late as compared in the early period, in which the late-treated serve as controls when estimating the effect on the early-treated; and four, those treated early vs. those treated late as compared in the late period, in which the early-treated serve as controls when estimating the effect on the late-treated (Callaway and Sant’Anna, 2019; de Chaisemartin and d’Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). One important concern that rises out of this analysis is the potential for negative weights on certain estimates to bias the overall treatment effect. In Figure D.1, we show the estimates and weights of all the different cells, calculated using the Stata command *bacondecomp*. This analysis shows two main features of our analysis: one, as in Carey et al. (2020), the largest weights are exclusively from the comparison of the never-treated and the treated. Two, there are no estimates with visibly negative weights. Using the method of de Chaisemartin and d’Haultfoeuille (2020), we can calculate the total number of negative weights using the entire sample. This shows that 15% of the weights in the full sample are negative, and the sum of the negative weights is only -0.036 , more than an order of magnitude smaller than the cases that paper identifies as problematic; the distribution of estimates and weights suggest our results are robust to their exclusion.

We can also use the alternative estimator proposed in de Chaisemartin and d’Haultfoeuille (2020) to generate tests of the parallel trends assumption as well as alternative estimates of our main coefficients. In Figure A.2, we present coefficient estimates for eight placebo periods (prior to the treatment, at time 0) estimated using the command *did_multiplt*. This shows no evidence of a violation of the parallel trends assumption. Using this command to estimate our main results from Table 2, we find positive and statistically significant estimates which vary slightly in magnitude

Figure D.1: Estimates and weights of our difference-in-differences analysis



Note: this figure shows the estimates and their respective weights for our main analysis, using the Stata command *bacondecomp*. Note that this analysis requires a balanced panel for implementation. As a result, we drop more than half of our observations, as many colleges lack data in one or two years. Nonetheless, the overall estimate of 0.055 is very similar to the estimate of 0.057 in our main analysis, shown in Table 2.

from our original estimates: for the full sample of name changers (i.e., column 1), we estimate $\beta_1 = 0.0439$, $se = 0.00856$. For only those who change from college to university (column 2), we estimate $\beta_1 = 0.0570$, $se = 0.00928$. We also use the alternative estimator from Borusyak et al. (2021), which generates estimates of roughly similar magnitude (column 1 $\beta_1 = 0.0552$, $se = 0.00401$; column 2 $\beta_1 = 0.0895$, $se = 0.00535$). Overall, we conclude from this analysis that the problem of negative weights described in these studies, driven by heterogeneity across time in the treatment effect and composition of the treated and control groups, does not appear to substantially bias our estimates.

E Comparing name changing colleges to elite colleges

Each year, colleges compete for students. As a result, our estimates are comprised of two components. Component one comprises name-changing colleges' success in attracting students who otherwise would have attended similar schools. Component two comprises these colleges' success in attracting students who otherwise would have attended higher-ranked, more competitive schools.

In this appendix, we attempt to isolate component two by restricting the comparison (or “untreated”) group to two alternative control groups much less likely to be affected by competition from colleges which changed their names over this period. First, we use an elite group of colleges defined by the “Project 211” policy as our untreated group of colleges.⁵⁶ None of the colleges in this group changed their names during our sample period (2006-2016). Furthermore, since the average ranking of name-changing colleges in our sample was 313, and the average ranking of these elite colleges was 60, the name changes that occur in our study period are unlikely to attract most students who would otherwise have enrolled at an elite college.

We show our results in Panel A of Table E.1. Our estimate of the impact of a name change on CEE scores, relative to the average CEE scores of students enrolled in elite colleges, is a smaller but still statistically significant gain of 0.015-0.020 SD. This is consistent with the notion that our estimates of the overall impact of name changes on CEE scores partly reflect the zero-sum nature of competition for students between similarly ranked colleges. Taken literally, this suggests that component two – the part of our estimates coming from name changes allowing colleges to attract students who would have otherwise gone to higher-ranking colleges – comprises roughly one quarter of the total effect. Through this lens, the other three quarters comes from these colleges attracting students from competitor colleges.

In Panel B of this table, we show results from an alternative strategy, expanding the control group to be all Tier 1 colleges which did not change their names. These colleges are a larger

⁵⁶In 1995, the “Project 211” policy was created to identify 100 colleges with high levels of research standards who would prepare China for the 21st century. The moniker was a concatenation of these goals: 21st century + 100 universities → “Project 211” (Yu et al., 2012). This group was later expanded to incorporate additional institutions.

group, similar to the combined group of large research institutions and elite liberal arts colleges in the US, and their average ranking is 123, somewhat lower than the Project 211 colleges. The coefficients we estimate here are larger in magnitude than those in Panel A, consistent with there being some competition between Tier 1 colleges who did not change their names and the group of all colleges which changed their names over this period. These estimates, however, are much smaller than those in columns 1 and 2 of Table 2, reflecting the fact that many of the colleges which change names are much lower ranked than Tier 1 colleges, and thus unlikely to compete with them for students.

Table E.1: Using elite colleges only as the comparison group

| <i>Panel A: Project 211 universities as comparison group</i> | | |
|---|----------------------------|---------------------------------|
| | (1) All name changes | (2) College to university |
| Effect on average CEE score (in SD units) | 0.015*** (0.004) | 0.020*** (0.005) |
| Adjusted R-squared | 0.935 | 0.892 |
| Number of observations | 148,976 | 106,194 |
| <i>Panel B: Tier 1 institutions without name change as comparison group</i> | | |
| | (1) All name changes | (2) College to university |
| Effect on average CEE score (in SD units) | 0.029*** (0.004) | 0.037*** (0.005) |
| Adjusted R-squared | 0.931 | 0.877 |
| Number of observations | 181,533 | 138,758 |

Note: this table shows the effects of college name changes on the mean CEE scores of students enrolled in the college, compared to the scores of students enrolled at elite colleges who did not change their names over this period. Panel A uses all “Project 211” colleges as the comparison group. Panel B uses all “Tier 1” colleges which did not change their names as the comparison group. These groups are further described in the text. The row entitled “Effect on average CEE score” reports the results for estimating β_1 in Equation 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F Student beliefs about name changes and their effects

In Section 3 we establish that college name changes influence college choice, that these effects have greater impact for attractive but misleading college name changes, and that greater effects appear for the college choice of applicants with less information about the college. In Section 3.5, we present analysis of text from one of China’s main online message boards to guide our interpretation of these effects and the role of information asymmetry in driving them. Here we present additional analyses of these text data, characterizing three key phenomena: i) applicants’ knowledge of the college name change phenomenon; ii) their beliefs about how these changes affected their college choice; and iii) the correspondence (or disconnect) between their beliefs about various traits of the college at the time of choosing and the reality they encounter when they arrive.

F.1 Data

We analyze text from online discussions on the website www.zhihu.com, the largest Q&A platform in China. Zhihu.com is similar to the popular English-language Q&A site quora.com, and is one of the most popular social media platforms among young people in China. The unit of observation we study is a “reply” to a posted question. We searched zhihu.com’s discussion boards for text containing any of a set of keywords relating to college name changes.⁵⁷ Our search identified 262 related questions and 5,163 replies/comments, the text of which we then scraped from the website. We exclude replies which focus on i) the general possibility of colleges changing their names, as opposed to specific college name changes; ii) colleges which previously granted only three-year degrees (in Mandarin, *dazhuan*) upgrading to be able to grant four-year degrees (in Mandarin, *benke*); and iii) college mergers. This generates a dataset of the text from 3,005 replies to questions involving the name changes of 226 colleges. We also scraped meta-data from the website on the number of likes, comments, and views, respectively, that these replies received. At the time of scraping, the replies that comprise our data had been read a total of 20 million times, received

⁵⁷These keywords were: *daxue gengming*; *daxue gaiming*; *xueyuan gengming*; *xueyuan gaiming*; *gaoxiao gengming*; and *gaoxiao gaiming*.

roughly 40,000 likes, and had more than 22,000 posted comments.

The most common topic in these replies is colleges changing their names to include the word university. Specifically, among the 226 name-changing colleges mentioned in these discussions, roughly three quarters (74.3%) changed their names from college to university. The other threads discussed either public colleges whose name change did not include the change from college to university (14.2%) or name changes at private colleges (11.5%).

F.2 Data analysis

To analyze these data, we first read through the discussions, manually identifying specific keywords related to five categories: i) the information gap between students' beliefs about what name changes imply and what actually happens in reality when a college changes its name; ii) actual resource changes at name-changing universities; iii) the impact of college name changes on the average CEE scores of students who choose to enroll at the college; iv) the impact of name changes on the employment prospects of graduates; and v) the putative "success" of the college's name change in improving its reputation. We identified these categories through inspection of the set of approximately 4,000 words that appear at least ten times in the data. Within each category, we then classified keywords by hand coding a set of 500 randomly selected replies. We list the specific keywords in each category in Table F.1. We link all threads discussing a given college to the various traits of its name change, such as whether the change included the shift from college to university, or whether the name change included a change in geographic scope.

We first describe the patterns we observe in the data and provide a few illustrative anecdotes. We then present a series of analyses of the conditional correlation between college name change types and traits of the content of the text. We conduct this analysis by estimating ordinary least squares regressions of each outcome Y for a given discussion i , on: a constant; an indicator for whether the name change includes the change from college to university ($Univ_i$); an indicator for whether the college is a private college whose name change severed the link to the parent college ($PrivSever_i$); and a series of controls (X_i) for college type, affiliation⁵⁸, and the size of the city in

⁵⁸The affiliation is the supervising body for the college, usually either the province government or province bureau

Table F.1: Keyword classifications for text analysis

| Dimension | Keywords |
|---------------------|--|
| Information gap | 混淆, 忽悠, 误导, 唬人, 噱头, 吸引, 坑, 骗, 诱惑, 听起来, 误以为, 误认为, 好听, 厉害, 霸气, 牛逼, 牛掰, 高大上, 高端, 档次, 名头, 逼格, 地域, 省内, 外省, 省外, 外地 |
| Resource change | 发展, 提升, 资源, 实力, 规模, 新校区, 师资, 教师, 老师, 教授, 院士, 人才, 科研, 学科, 硕士点, 博士点, 经费, 教学, 教学质量 |
| Gaokao score change | 高考, 招生, 录取, 报考, 生源, 分数, 成绩, 填志愿 |
| Employment | 毕业生, 工作, 牌子, 平台, 声誉, 招聘, 待遇, 面试, 简历 |
| Success | 成功, 失败, 不错, 上档次 |

Note: this table shows the keywords used for our analysis of text data described in discussion boards on the website zhihu.com.

which a college is located.⁵⁹ Our estimating equation is:

$$Y_i = \tau_0 + \tau_1 Univ_i + \tau_2 PrivSever_i + \tau_3 X_i + \varepsilon_i \quad (4)$$

By estimating the parameters τ_1 and τ_2 in Equation 4, we test two specific hypotheses. Estimating τ_1 allows us to gauge whether college names which include a change from college to university attract more attention, approval, or positive sentiment. Similarly, estimating τ_2 tells us whether private colleges whose name changes sever their ties to the parent college attract more attention and are seen differently than other changes.

Our outcome measures capture either the popularity or the sentiment of replies. We use two popularity outcomes and two sentiment outcomes. For popularity, we use the number of likes and the number of comments. For sentiment, we use whether the replies contained keywords relating to education. We use this to absorb some of the secular heterogeneity in baseline views about colleges from different places and backgrounds.

⁵⁹The possible values of college type are: comprehensive college; technological college; economics or finance-focused college; medical college; and others. The possible values of college affiliation are Ministry of Education; other Ministries; and local government. The possible values for size of city of college location include municipality-level city; provincial capital or large city; and small or medium-sized city.

to the success of the name change in raising average CEE scores, and a measure of overall positive sentiment in the text. For number of likes and number of comments, the outcome variable is the log of one plus the raw value. The success and positivity outcomes are measured as indicator variables. Success is equal to one if the text contains a keyword related to perceived success of the name change, and positivity is a variable classified as $[0 = No, 1 = Yes]$. It is generated by the Baidu Sentiment Analysis AI platform, which allows users to input text and renders classification of sentiment within the text based on an AI algorithm trained on billions of Chinese-language documents.⁶⁰

F.3 Results

We first report descriptive analyses of these data. The most common keywords contained in these threads relate to the information gap. Specifically, among the 3,005 discussions used in our analysis, 336 (11.18%) of them include keywords in the information gap category. Close reading of the text in these discussions reveals that new college names appear more appealing to applicants than old ones, with some discussants even saying that they would not apply to a college if it were still using its old name. For example, one respondent said: “if Taishan Medical College did not change its name to Shandong First Medical University, I would never apply to this school.” See Table A.10 for this and other anecdotes from the text data that illuminate these and related patterns.

In these 336 threads containing keywords pertaining to the information gap, 52 (15.5%) of them contain comments asserting that new college names are likely to be most appealing to students from outside of the province in which the college is located. Furthermore, many discussants asserted that new college names attract high-scoring students from other provinces but are less likely to “cheat” students from the same province as the college. This corroborates our interpretation of the within-province vs. out-of-province heterogeneity in effect size (shown in Table 4): that among applicants from outside of the province in which the college is located, there exists a larger information gap between applicant beliefs about quality and the reality of the quality of the college, than exists among applicants from within the same province.

⁶⁰Available at https://ai.baidu.com/tech/nlp/sentiment_classify.

The gap between students' beliefs and reality extends to the geographic location of the college. Fifteen of the 336 information gap discussions report the experience of students who incorrectly inferred the location of the college they chose from the college's (new) name. Specifically, these colleges changed their names to contain either the name of the province or a reference to China (e.g., *zhong hua*). Because of this, applicants assumed the colleges were located in the provincial capital when, in fact, they were located in smaller, more remote prefecture-level cities. These discussions noted that this information gap allows these colleges to attract students with higher CEE scores than the college would normally be able to recruit. This is borne out in the estimates we show in Panel A of Table 3, which show that alluring but misleading name changes have a large effect on college choice, and Panel B of Table 4, which shows that these effects are larger for out-of-province applicants.

In addition, within these discussions relating to the information gap, there was discussion of 13 private colleges which dropped the name of their "parent" college from their names (see description in Section 3.4). In these discussions, there was explicit mention that eight of these name changes made the college less attractive. Some discussants, especially those from other provinces, said that they applied to these colleges because of the high quality of the parent college. This suggests that parent college names may be a symbol of high-quality college education, despite the fact that the resources and management of independent colleges has nothing to do with those of the parent institution.

The text in our data are far less likely to contain discussion of whether there are changes in college resources coinciding with college name changes. Among the 3,005 discussions used in our analysis, only 57 (1.90%) discuss possible resource changes. This low prevalence may reflect the fact that few resources change when a college changes its name or that students know (or care) little about the resource changes associated with name changes. Furthermore, among these discussions of resource changes, two thirds (38) indicate that almost no resources change at the time of college name changes. Only one third (19) indicate that some resource changes happen after name changes. These discussions of resource changes cover new campus openings, scientific

research, faculty quality, and financial budgets.

Next, we report analyses of the relationship between the traits of different colleges' name changes and the traits of the text discussing them. We report our main results in Table F.2. In this table, each column corresponds to a separate estimation of Equation 4, showing the conditional correlation between two dimensions of college name change type and the four outcomes. We study these correlations for two name change traits – the change from college to university and the change for private colleges who sever their ties to their parent college – relative to all others, as described in the row labels. The column headings describe the dependent variable being studied.

For assessed success and sentiment, we see divergent results consistent with the signal sent by the different types of name change. For the shift from college to university, which signals a potential increase in prestige and resources, we see these changes are significantly more likely to be assessed as “successful” but find no evidence of a significant correlation with positive sentiment. For private colleges' name changes which drop the link to the parent college – a change which signals a loss of prestige and resources despite there being no actual change at the college – we see a statistically significant lower likelihood of both the assessment of success and of positive sentiment. These findings corroborate our results from Section 3, showing that name changes including college to university are generally more attractive to students than other changes, and that dropping the link from private college to parent college can have a negative impact on the average CEE scores of students who subsequently choose to go to the college. We also find that reply threads where the information gap is mentioned are 13.8 percentage points more likely to also mention an increase in CEE scores. Our results are robust to dropping discussions related to the most commonly discussed change, that of Luzhou Medical College changing to Southwest Medical University.

Table F.2: Text analysis results

| | <i>Attention received</i> | | <i>Content of discussion</i> | |
|--|----------------------------------|-------------------------------------|--|---|
| | (1) Log number of likes | (2) Log number of comments | (3) Name change perceived as successful | (4) Positive sentiment in comments |
| Change is from college to university | 0.243*** (0.076) | 0.172*** (0.071) | 0.197*** (0.035) | -0.026 (0.032) |
| Private college loses use of parent college's name | 0.293*** (0.109) | 0.308*** (0.107) | -0.181*** (0.062) | -0.148*** (0.046) |
| Number of observations | 3,005 | 3,005 | 1,341 | 2,877 |

Notes: this table reports conditional correlations between properties of the text in online discussions and college type. The unit of observation is a discussion about a given college. Each row represents an estimation of Equation 4, with the dependent variable given in the column title and the coefficients described in the row title. Among the 3,005 discussions used in our text analysis, one change, Luzhou Medical College changing its name to Southwest Medical University (SMU), is seen as controversial and attracted a disproportionate amount of public attention, accounting for 32.5% of our data. Our results are robust to excluding data related to SMU. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

G Analysis of Chinese civil service exam data

In this appendix we explore, observationally, whether people who graduate from a given college after its name changes possess different skills than those who graduate from the same college before the change. To do so, we use person-level administrative data from the written part of China’s civil service examination. Applicants to the Chinese civil service first complete an online application form and then sit for an annually held written exam. This written exam comprises two sections - a test of “administrative skill,” consisting primarily of multiple choice questions testing knowledge of arithmetic, the law, and decorum, and an essay prompt asking the respondent to design and describe a plan to address a hypothetical issue that might arise in the course of working for the civil service. Each year, all applicants in a given province take the same version of this written test.

We have administrative, individual-level data from over 53,000 test takers in 30 cities over six years. This data comprises applicants’ gender, their scores on the test - both overall, and the multiple choice and essay sections separately - and the name of the college from which they received their degree. We use this to conduct a simple descriptive analysis, estimating whether individuals graduating from a given college after it changes its name perform differently than individuals graduating from that same college in the years before the name change on these tests taken in a given year.

We implement this using the following estimating equation:

$$Score_{iltc} = \kappa_0 + \kappa_1 NewName_i + \kappa_2 Male_i + \kappa_3 \vartheta_{lt} + \kappa_4 \theta_c + \varepsilon_{iltc} \quad (5)$$

This regresses the score of individual i in locality l at year t and college c on: a constant; an indicator for whether they enrolled a given college after a name change occurred; their gender; a locality-year fixed effect ϑ_{lt} ; and a college fixed effect θ_c . We standardize the test scores to the city-by-year level. The main coefficient of interest is κ_1 , which estimates whether applicants enrolling in a given college, post-name change, perform any better than applicants enrolling in that

Table G.1: Civil servant exam scores and college name changes

| | (1) | (2) | (3) |
|---|--------------------------|----------------------------------|--------------------------------|
| | Overall test score | Administrative skill score | Government writing score |
| Graduated from college after name change | 0.075** (0.035) | 0.023 (0.035) | 0.070** (0.035) |
| Number of observations | 53,247 | 53,247 | 53,247 |

Note: this table shows results from estimating Equation 5 with the outcome being the civil servant exam test score described in the column heading. Each of these scores is standardized at the city-year level. Because different cities use different weightings of the essay and administrative skill scores to generate the overall test scores, and because we standardize the three test scores separately, the overall test score estimate is not a weighted average of the other two sub-test estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

same college before the name change.

This estimate is just the conditional correlation between the college's name at the time the person chose to enroll in the college and their subsequent performance on the test, rather than a causal impact of the name change per se. This is because who does or does not take the civil servant exam in a given year is endogenous, with individuals selecting in based on their current labor market prospects and interests. Nonetheless, the parameter is equivalent to what government hiring professionals observe regarding the association between college name changes and candidate quality.

We show our results in Table G.1. For all sections of the exam, the mean score of applicants listing the college's new name is higher than for applicants listing the old name. For both the overall score and the essay score, this difference is statistically significant. This suggests that, at least to government employers, college name changes are associated with observable differences in applicant quality. This is consistent with the results in Section 3 showing that college name changes were successful in attracting students with higher CEE scores.

H Details and further analysis of HR survey

In this appendix, we present further analysis of the survey of HR professionals described in Section 4.3. The survey consisted of 21 questions - 18 multiple choice, and three mixed: a multiple choice question followed by a free-response blank asking the respondent to explain their choice. To find participants, we used the professional network of one of our research assistants, a part-time MBA student who had previously worked as a HR professional. We sent the survey via the online messaging service *WeChat*, offering a gift card worth 2-10 yuan (\$0.30-\$1.50) as a gesture of gratitude. We sent the invitation out to 147 individuals and use data from the 87 HR professionals who responded.

These survey data contain a few key messages. First, in response to the question “if, in the process of looking through resumes, you find a college you are unfamiliar with, how would you deal with this?”, eighty-two of the 87 respondents reported that, in such a situation, they would look up the college online or ask a colleague about the college. Second, we learned that the majority of these professionals were aware of the college name change phenomenon we study: eighty-four claimed to be somewhat or very familiar with the phenomenon of college name changes. Together, these patterns corroborate our assumption that HR professionals are relatively well informed about the existence of college name changes. We also learned that these individuals thought that name changes would attract better students (53 of the 87 respondents) and that new names would help graduates on the job market (82 of 87 respondents).

The final two questions in the survey asked respondents the following hypothetical question – for each of two job types (programmer and administrative professional), if the person encountered two applicants who were observationally similar, but one listed the “college” version of a given college’s name, and the other listed the “university” version, which they would hire, and why? For the hypothetical situation of choosing a “college” graduate over a “university” graduate, the respondents suggested that the applicants listing the university name might be overqualified for the position, leading to dissatisfaction and possible loss of the employee after a short period of

time on the job. While, unconditionally, a larger number of the HR professionals we surveyed stated a preference towards candidates listing the university name and away from those listing the college one, these respondents are disproportionately from large, private companies. In such organizations, the risk of mismatch due to over-qualification is likely less of a concern than in companies and organizations other parts of the Chinese economy.