



## (Mis)Information and the Value of College Names

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Hundreds of colleges have changed their names to signal higher quality. We estimate how this affects college choice and the labor market performance of college graduates. Administrative data show that name-changing colleges enroll higher-aptitude students, with larger effects for attractive-but-misleading name changes and among students with less information. A resume audit study shows that employer callbacks respond to the increased aptitude of recruited students at these colleges. We broaden these results using scraped online text data, survey data, and other administrative data. Our study demonstrates that signals designed to change beliefs can have real, lasting impacts on market outcomes.

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## Abstract

Hundreds of colleges have changed their names to signal higher quality. We estimate how this affects college choice and the labor market performance of college graduates. Administrative data show that name-changing colleges enroll higher-aptitude students, with larger effects for attractive-but-misleading name changes and among students with less information. A resume audit study shows that employer callbacks respond to the increased aptitude of recruited students at these colleges. We broaden these results using scraped online text data, survey data, and other administrative data. Our study demonstrates that signals designed to change beliefs can have real, lasting impacts on market outcomes.

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# 1 Introduction

The information people possess affects the choices they make, the outcomes of market transactions, and even the existence of markets (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 contain misinformation.

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 often hinge upon people’s beliefs about a school’s quality (MacLeod and Urquiola, 2015; MacLeod et al., 2017). Knowing this, colleges frequently 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 like dormitories or cafeterias (Winter, 2003; Alter and Reback, 2014; Newlon, 2014).

The signals we study are college name changes which attempt to change beliefs about college quality. College name changes are very common, both in the history of the US higher education system as well as in contemporary higher education in the US and across the world. Many elite in-

stitutions 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 past few decades, over 1,200 colleges have changed their names in the US and China alone. In the US, more than 530 "mainstream" institutions have changed their names since 1996 (Clark, 2009). These name changes 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; Platt et al., 2017; Clinton, 2020).<sup>1</sup> In China, the context we study in this paper, more than seven hundred Chinese 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.<sup>2,3</sup> 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 the information people do, or do not, possess.

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<sup>1</sup>Several hundred 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).

<sup>2</sup>More than half of the name-changing colleges we study face no legal requirement regarding college resources or staffing in order to receive permission to change their name. Among the remaining colleges which do face such requirements in order to change their names, for many of 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 for preparing its application for permission to change its name. When the college believes it is ready for review, it sends its application materials to the Ministry of Education (MOE). The MOE then processes the application, sends an inspection team to the college, and, after review, issues its final approval decision the following year. Therefore, even if a college deliberately improves its facilities or resources in order to meet the MOE requirements, such changes are highly unlikely to happen in the same year as its approved name change.

<sup>3</sup>In this way, the setting we study is similar to the study of college mergers in Russell (2019). It is also similar to Clinton (2020), who reports the effects of a state-mandated change of name from college to university for six colleges in Massachusetts, where no resources were allocated to help with the transition. That paper focuses on the labor market performance of students who had entered these colleges prior to the name change, but graduated afterwards, whereas ours focuses primarily on how name college changes affect college choice and graduates' subsequent labor market outcomes.

We use the case of China because it is unique on two key aspects that facilitate our study of college choice, and because the size of its labor market allows us to conduct a large resume audit study. First, China has the largest market of college students in the world<sup>4</sup> 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 provides us a unique opportunity to precisely estimate how college efforts to change their reputation affect whether they are able to attract higher quality applicants. Finally, China’s labor market is very large and, similar to the US, hundreds of millions 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 between 2006 and 2016, a period in which more than 200 colleges changed their names.<sup>5</sup> We focus only on institutions with permission to grant bachelor’s degrees, excluding institutions that upgraded from primarily granting three-year degrees to granting four-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 find 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 misinformation – 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

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<sup>4</sup>In 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](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](https://nces.ed.gov/programs/digest/d19/ch_3.asp). Both accessed March 27, 2021.

<sup>5</sup>Shi 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 information, absolute vs. relative gain, resources, and labor market consequences that we engage with here. At the end of Section 3.3 we further describe how our findings relate to this paper and a few other related studies.

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. Furthermore, some students report being deceived by the college name changes we study. For example, many report being misled by new college names 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 changes in college choice induced by 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 the premium to listing a college's new name, as opposed to its old one. We send resumes in pairs: in each pair, both applicants will have attended the same college, but the college name listed varies across resumes.

Our results suggest employers can see that college name changes increase the aptitude of the students these colleges recruit. 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, we observe a 15 percent penalty in the likelihood of receiving a callback for resumes listing a college's new name. The penalty is greater in jobs with lower credential requirements and those offering lower pay, and greater for applicants from higher ranked colleges. 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 fear pursuing "overqualified" applicants who are difficult to recruit and retain, and who might underperform on the job because of mismatch.<sup>6</sup> By contrast, we find that in jobs with greater requirements for technical skill or experience, applicants listing a college's new name are six to ten percent more likely to receive a callback, though these

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<sup>6</sup>In 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.

differences are not statistically significant.<sup>7</sup>

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 of HR professionals reveals that those making hiring decisions see a similar increase in applicant quality, and more broadly are aware of college name changes and their effects on college choice. As a result, they believe that 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 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 (mis)informative signals, and names in particular, in markets with information frictions. People often use names to infer the characteristics of products and firms. A wide literature in economics has shown that the names of firms, products, and even people 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

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<sup>7</sup>Our resume audit study has similar or greater statistical power than many other prominent resume audit studies (Bertrand and Mullainathan, 2004; Deming et al., 2016; Agan and Starr, 2017). Nonetheless, reducing the sample size by a factor of four for each of these comparisons increases the minimum detectable effect proportionately.

name changes have affected the college choice of tens of millions of students across the US, China, and other countries to date, and will affect the lives of tens of millions more in the next few decades.<sup>8</sup> Our findings show that while these changes affect college choice behavior, they are also perceived in the labor market as increasing average graduate aptitude.

The paper proceeds as follows: Section 2 explains the setting we study and our main empirical predictions. Section 3 presents our analysis of how college name changes affect college choice. Section 4 presents our analysis of how college name changes affect performance in the labor market. 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 8 and 11 million students per year (Yu et al., 2012). In this section, we describe the history and institutional details of college name changes in China and how this relates to applicants' college choice behavior.

### 2.1 College name changes in China

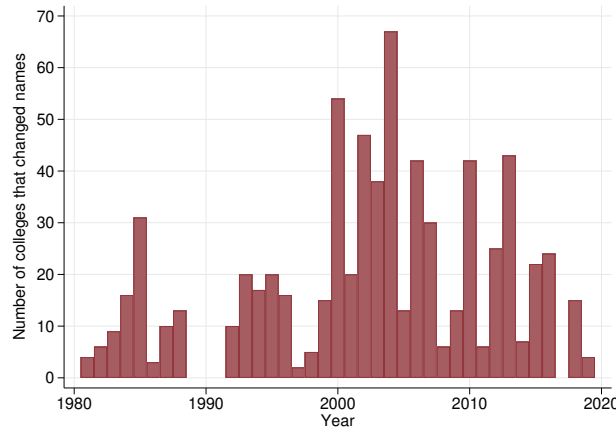
China's most prestigious institutions, such as Peking University and Tsinghua University, were founded between the late 19th and early 20th centuries. Many colleges were founded later, in the period immediately after the founding of the People's Republic of China in 1949. When these schools were created, 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 En-*

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<sup>8</sup>Using 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 over 25 million students were affected by these name changes, over this period, in these two countries alone.



Figure 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.

*gineering*.<sup>9</sup> 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.

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 1, we show a histogram with the number of name changes by year, from 1980 – when this phenomenon began – until today. 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. Many of these name changes were likely initiated by college leaders in a bid to improve the quality of the college’s applicants, partly as a way to further the leader’s own career. The leaders of Chinese public colleges – including both presidents and communist party secretaries, the two highest positions at a college

<sup>9</sup>Two 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.

– are 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).<sup>10</sup>

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 degrees (in Chinese, *dazhuan*) to primarily granting four-year degrees. We also exclude institutions which merged with others during this period. At the start of our study period, name-changing schools spanned from the first percentile to the sixtieth percentile of rank (with the 99th percentile being the top ranked schools). We discuss heterogeneity in effects by rank in Section 3.

## 2.2 Types of name change

There are multiple types of name change, which we summarize in Table 1. The most common is the switch from “college” (*xueyuan*) to “university” (*daxue*) – type 1 in Table 1. Another common change increases the geographic scope, e.g., swapping out a city’s name for that of a province, as was the case when the *Xuzhou Normal University* became the *Jiangsu Normal University* (type 2). Similarly, colleges can change the professed scope or focus of the college’s specialization, as the *Zhejiang College of Education* did when it became the *Zhejiang College of International Studies* (type 3). These can also be combined, e.g., changing the geographic scope and changing from college (*xueyuan*) to university (*daxue*), as did *Zhuzhou College of Technology* when it became *Hunan University of Technology*, Zhuzhou being a city within Hunan province (type 4).

There is a similar and common phenomenon of college name changes in the US, which often include the change from college to university. In Appendix A we describe the similarities and differences between the two contexts. We argue that, on balance, the similarities between name changes in the two contexts highlights the broad policy relevance of our analysis.

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<sup>10</sup>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). An article from 2016 in the China Youth Daily describes how the bureaucrats who run colleges may feel pressure to use name changes to improve their own careers (<http://cpc.people.com.cn/pinglun/n1/2016/0119/c78779-28066724.html>, accessed September 5, 2021).

Table 1: Types of name change

<i>Type</i>	<i>Description</i>	<i>Name</i>	<i>Example</i>
1	Institute/college to university	Old New	Shanghai College of Electric Power Shanghai University of Electric Power
2	Change in geographic scope	Old New	Xuzhou Normal University Jiangsu Normal University
3	Change in industrial focus	Old New	Zhejiang College of Education Zhejiang College of International Studies
4	Changes to more than one aspect	Old New	Zhuzhou College of Technology Hunan University of Technology

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

Finally, we study name changes among private colleges in China in addition to those in public colleges. 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. For example, the University of Science and Technology Beijing - Tianjin College (*Beijing Keji Daxue - Tianjin Xueyuan*) is one such private college. These private colleges are generally seen to be of lower quality than the “parent” public college with which they are associated. Name changes at these colleges normally occur due to a change in the parent college’s name, which is unrelated to any choice the private college might make.

### 2.3 What happens when a college changes its name?

Colleges must apply to the Ministry of Education (MOE) for permission to change their names. Among the institutions we study, there are two distinct cases. The first case comprises institutions that change their names, but whose name change does not include the deliberate change from college to university. For these schools, there are no government-set standards for the school to meet; in other words, this is primarily re-branding. In our data, 135 of the 244 colleges fall into this category.

An important sub-case within this case is for private colleges whose parent college changes its name. For these colleges, the name change happens without any choice or action on the part of the institution. In some cases, the college is allowed to keep its link to the parent college, meaning that its name improves. In other cases, the college is forced to sever its ties to the parent college, leading to a drop in the attractiveness of the name. We study each in turn.

The second case is schools whose name change does include the change from college to university. For these colleges (109 of the 244 changes we study), there are government-set standards for what constitutes a university that the institution must meet. To be called a university, the institution must satisfy two sets of requirements.<sup>11</sup> 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.<sup>12</sup> 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.<sup>13</sup> Once these requirements are met, a college must prepare and submit an application by the annual deadline, usually around October 1st. The MOE then reviews applications and conducts site visits; it issues decisions in the spring of the following year, and the name changes it approves occur in the months thereafter. The total process therefore spans several stages. The college decides to attempt to change its name; it begins preparing its application materials – especially, ensuring their research productivity and resources meet requirements; it submits its application; the MOE reviews

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<sup>11</sup>Chinese college name changes did 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. At most, name changes may have increased the number of post-bachelor's degree options. 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 name changes in the US also occur without substantial changes to facilities, offerings, or other characteristics (Finder, 2005; Platt et al., 2017; Wong, 2019; Acton, 2021; Clinton, 2020).

<sup>12</sup>We provide more details about these requirements in Appendix B.

<sup>13</sup>A recent piece by Jiachuan Chen, the president of Qilu University of Technology, documents that the school spent more than ten years working to change its name from Shandong College of Light Industry to its current name. 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 November 26, 2020.

the application; and the MOE makes its ultimate decision. The full process takes several years.

We show empirical evidence of the extent to which college resources change at the time a college changes its name in Appendix C. We find no evidence of changes in a wide range of different measures of college resources in the year in which the name change occurs. We conclude that, for the first two cases, in the year that a name change is first observable to college applicants, very little else about the college is likely to have changed.<sup>14</sup>

## 2.4 College admissions in China

College admissions in China depend on three core factors: the student's score on the college entrance exam, the student's expressed preferences over colleges, 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 exam occurs once each year. In it, all students are tested on core subjects (Chinese, math, and a foreign language) along with subjects specific to their track (science or humanities). Students take the exam and express their preferences over colleges.<sup>15</sup> The admissions system matches students to colleges using province-specific assignment mechanisms; in all assignment mechanisms, students compete with other students from their province and in their high school track for admission to a given college (Zhang, 2016; Chen and Kesten, 2017; Jia and Li, 2021). If they are matched to a college, the student is 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, the student will not be able to attend college that year.

Chinese high school students make college choices with imperfect information. As in the US, many dimensions of college quality are unobservable. Students receive only suggestive information about the likely admissions cutoffs for their current application cycle<sup>16</sup> and state their college

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<sup>14</sup>Similarly, in a study of the price effects of college mergers in the US, Russell (2019) 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.

<sup>15</sup>The sequence of this 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 within each of the cells we analyze.

<sup>16</sup>In a given year, the admissions cutoff for a given school depends on the demand for that school. The minimum

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. (2016) show that poor and rural students make particularly sub-optimal choices, reflecting either limited knowledge of colleges far from their hometown or greater preference for staying close to home for college. College name changes, therefore, may have a larger effect on students with less information.

We further characterize the process of students’ college choice using a survey given to the entire entering class of students in the 2014-15 academic year in a large, anonymous Chinese college.<sup>17</sup> This survey asked respondents which factor most influenced their choice of college. Other than the student’s CEE score, which mechanically determines where a student can attend college, the school’s reputation (*shengwang*) was the most common factor given, with 337 of the 2,611 students selecting this (30% of those who did not mention the CEE score).<sup>18</sup>

## 2.5 Expected effects

In this section, we outline our ad-ante expectations for how college name changes will affect the decisions of college applicants and, separately, employers seeking to hire college graduates.

*Expected effects for college applicants.* Because college applicants generally have imperfect information about college quality (Dillon and Smith, 2017; Bo et al., 2019; Mulhern, 2021)<sup>19</sup>, we expect college applicants’ choice of college to be swayed by college name changes.<sup>20</sup> This comes

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admissions score for a given applicant province-college-track cell 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).

<sup>17</sup>This college is in the “Project 211” classification ([https://en.wikipedia.org/wiki/Project\\_211](https://en.wikipedia.org/wiki/Project_211)).

<sup>18</sup>In this and another survey of college students in various colleges administered in 2009 (the *daxuesheng chengzhang zhuizong diaocha*, or “CSDPS”), respondents were asked who was the most important influence in their choice of which college to attend. Roughly half of students (47-48%) in both surveys listed themselves, followed by parents or other family members (35-40%), and then teachers, friends, and other non-family members.

<sup>19</sup>Hoxby and Turner (2015) report a US-based survey of high-achieving, low income students’ knowledge about their college choices. They find that these students lack information about “net prices, instructional resources and rigor, student bodies, and curricula.” The authors 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.

<sup>20</sup>Hoxby and Turner (2013) show that that college choice is affected by concerted doses of information; other work shows that salient but seemingly uninformative news – such as small changes in the school’s placement in third

from two separate sources. One source is the fact that the name change signals higher quality. The applicants may infer that the school has more or better resources because of its new name. Though we see no changes in resources, resources are difficult to observe and so more appealing names – a broader geographic scope, a more appealing industrial focus, or using the name university instead of college – may cause applicants to change their beliefs about the institution’s quality.

The other source is a potential increase in the quality of the peer group at that institution. This source has a “general equilibrium” flavor to it: if applicants anticipate that the name will attract other applicants with higher aptitude, it is rational for them to also infer a likely increase in the quality of that college. Furthermore, applicants can observe the average college entrance exam score among students enrolled at the college in the previous year.<sup>21</sup> As a result, any initial increase in entrance exam scores caused by the change in college name constitutes an increase in actual college quality, particularly given the importance of peer effects in student outcomes (c.f., Sacerdote et al., 2011). This makes any initial gains from a college name change likely to persist over time.

The most important dimension of heterogeneity we anticipate among applicants is by baseline information. Specifically, the less information an applicant has about the college, the more their beliefs about a college’s quality will be affected by a change in name.<sup>22</sup> Because of this, we would expect “low information” applicants’ choices to respond more to these name changes than those of applicants with more information.

*Expected effects for employers.* Employers have substantially more information about college quality than college applicants. The HR professionals responsible for making hiring decisions have already graduated from college, and their main professional responsibility is to gather information about applicant quality and make decisions based on this information. If college name changes

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party rankings or close victories in college sports – can also have detectable effects on college application behavior and matriculation (Pope and Pope, 2009; Alter and Reback, 2014). Other studies of middle school choice and high school choice suggest that small doses of information can lead to observable changes in school choice (Hastings and Weinstein, 2008; Andrabi et al., 2017).

<sup>21</sup> See Section 2.4 for more details on this score and other general information about the system.

<sup>22</sup> This comes from the basic intuition behind bayesian updating: the less informed a person’s prior is, the larger their update will be to a given amount of new information.

generate differences in student quality over time, employer decisions should reflect this. Note that this could affect callbacks positively or negatively. For the majority of jobs, we would expect applicants listing a college’s new name to be more likely to receive callbacks than those listing the old name. On the other hand, in jobs where there is greater risk of hiring an over-qualified candidate—i.e., jobs with lower status or salary, in which highly qualified applicants might be dissatisfied and, as a result, under-perform or be more difficult to retain—applicants listing a college’s new name might be *less* likely to receive a callback. Recent resume audit studies in the US, India, and China have found that employers regularly avoid recruiting overqualified applicants, particularly in lower-status and lower paying jobs (Deming et al., 2016; Chen, 2019; Sekhri, 2020). Similarly, we anticipate this behavior will appear more in the types of jobs with lower requirements for technical skill, lower credential requirements, and lower experience requirements.

### **3 How do college applicants respond to name changes?**

In this section, we study how college applicants respond to college name changes. 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). We use a difference-in-differences research design to estimate how name changes affect the aptitude of the students these colleges recruit, as measured by the CEE scores of enrolled students at name changing colleges, compared to those at essentially all other colleges in the market for these applicants.

#### **3.1 Data**

Our main dataset is college-level CEE score information scraped from a leading educational website, “China Education Online” ([www.eol.cn](http://www.eol.cn)). The administration of this site is supervised by China’s Ministry of Education. We limit our analysis to colleges that are qualified to issue bach-



elor's degrees<sup>23</sup> 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.

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.<sup>24</sup> 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.<sup>25</sup> Because test questions vary each year and, within a year, vary across provinces and across tracks, we standardize test scores at the province–year–track level.

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](http://baike.baidu.com), a Chinese analog to Wikipedia.com. Among the 1,198 colleges in our analysis, 244 colleges (20.4 percent) changed names between 2006 and 2016. We also collected data on enrollment quotas at the province–year–track level from 2008 to 2015, scraped from another leading educational website in China.<sup>26</sup>

### 3.2 Empirical strategy

We use a difference-in-differences (DiD) design to estimate how college applicants respond to college name changes. 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 and 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.<sup>27</sup> Our

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<sup>23</sup>This is primarily to allow us to focus on a single market: that for bachelor's degrees. The market for associate's degrees is a separate market of interest left to future research.

<sup>24</sup>As mentioned in Section 2, students in a given track only compete for admission with other students from the same province. Note also that minimum scores are set annually by the government at the province-track-tier level, but in most cases this is not binding, as the minimum score at a given institution is determined by the demand for that particular college-track-tier combination in that year.

<sup>25</sup>Over the period of our study, each major–track–college–province cell was assigned to one of three tiers, and admissions in each cell are subject to students reaching the tier-specific minimum CEE score set by the Ministry of Education.

<sup>26</sup>The website – <http://www.gaokao.com/> – also focuses on China's college entrance examination.

<sup>27</sup>This approach differs from other applications of the DiD design which identify a specific comparison group. In our use of the DiD, we are comparing name-changing institutions to all other institutions in the market for college applicants, thus avoiding the concern that a deliberately selected subgroup may be an inappropriate comparator. See Callaway and Sant'Anna (2019) and Goodman-Bacon (2021) for further discussion of these issues. Note also that, as

main estimating question is:

$$y_{cpstr} = \beta_0 + \beta_1 NewName_{ct} + \beta_2 s_{cptr} + \beta_3 r_{cpst} + \theta_c + \mu_t + \eta_p + \varepsilon_{cpst} \quad (1)$$

The variable  $y_{cpstr}$  is the mean CEE score for a given college  $c$ , of students 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.<sup>28</sup>

Our main coefficient of interest is  $\beta_1$ , the impact of a new name on the average CEE score of 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 crucial to our identification strategy. The first is the set of fixed effects at the college level,  $\theta_c$ , to ensure that we are comparing only within a given college, across time. The second is the set of year fixed effects,  $\mu_t$ , which removes variation from time trends secular to changes in college names. The third is the set of province-level fixed effects,  $\eta_p$ , which ensures that we are comparing only among applicants from within a given province, the level at which applicants compete.<sup>29</sup> 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 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 ( $r_{cpst}$ ) because, within a college and within a track, majors in different tiers have different minimum score requirements.<sup>30</sup>

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

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a result of our comparison with the entire market, 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.

<sup>28</sup>Our main results are robust to instead clustering at the (more conservative) college level.

<sup>29</sup>All of our results are robust to using province-by-year fixed effects instead of province and year fixed effects separately.

<sup>30</sup>Tier 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.

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 event study, which shows no evidence of a statistically significant difference in test score trends prior to changes in college names. We show an alternative test of this, using the method in de Chaisemartin and d’Haultfoeuille (2020), in Figure A.1, which also shows no evidence of violation of the parallel trends assumption.

A series of recent papers have shown that difference-in-differences estimates of policies or programs with staggered rollout may suffer bias from negative weights assigned to some components when implemented with a two-way fixed effects approach such as the one we specify here (Callaway and Sant’Anna, 2019; Sun and Abraham, 2020; de Chaisemartin and d’Haultfoeuille, 2020; Goodman-Bacon, 2021). In Appendix D, we conduct a series of robustness checks to assess the risk of this type of bias. These tests include the decomposition proposed in Goodman-Bacon (2021), the calculation of negative weights proposed in de Chaisemartin and d’Haultfoeuille (2020), and the alternative estimator also proposed in that paper. We find that our application has a small proportion of negative weights, and these contribute very little to our overall estimates. We show that our estimates are robust both to their exclusion, and to use of the alternative estimator from de Chaisemartin and d’Haultfoeuille (2020).

### 3.3 Main results

We present our first set of main results in Table 2. We present estimates of  $\beta_1$  for four sets of “treated” colleges. In column 1, we use all colleges who changed their names as the “treated” group. In column 2, we show results for the subsample of public colleges whose name change contains a shift from the word college (*xueyuan*) to university (*daxue*)<sup>31</sup>, and in column 3 we show results for public colleges whose name does not include this change. In column 4 we show results for private colleges. The name changes we study in columns 3 and 4 are particularly unlikely to be correlated with any real change in institutional resources or offerings; see Sections 2.2 and 2.3 for

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<sup>31</sup>In other words, all public colleges with type 1 and type 4 name changes, as described in Table 1.

Table 2: Overall effects of name changes on CEE scores of enrolled students

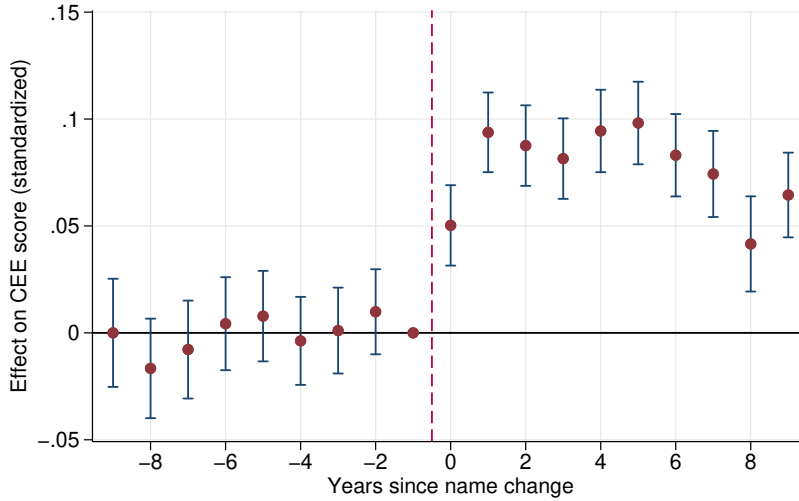
	(1)	(2)	(3)	(4)
	All college name changes	Public college, change does include college to university	Public college, change does not include college to university	Private colleges only (all change types)
Effect on average CEE score (in SD units)	0.057*** (0.003)	0.077*** (0.004)	0.036*** (0.009)	0.028*** (0.006)
Number of colleges that changed names	244	109	19	116
Total number of colleges in sample	1,198	1,198	1,198	1,198
Number of observations	418,441	418,441	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 CEE average score in SD units” reports our estimate of  $\beta_1$  in Equation 1 for the treated group named in the column heading. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

more detail.

We estimate that, on average, a change in college name is associated with a statistically significant increase of 0.057 SD in the average CEE score of the students who choose to attend the college (column 1). Among schools which changed their names from college to university, our estimated coefficient increases to 0.077 SD (column 2), suggesting that those colleges harvest a large increase in school reputation by adding the word “university” (*daxue*) to their names. Columns 3 and 4 show smaller but statistically significant estimates for public colleges whose name does not include this change and, separately, for private colleges. The sign and magnitude of our results are broadly consistent with related work showing how the release of salient, positive information about certain colleges in the US increases application rates to these colleges (Pope and Pope, 2009; Alter and Reback, 2014). We also estimate how these test score gains map onto changes in national rankings; 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

Figure 2: Event study - effects of name changes on average CEE scores over time



Note: this figure shows 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.

rise.<sup>32</sup>

In Figure 2, we show the event study for the analysis in column 2 of Table 2. This shows 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:

$$y_{cpstr} = \alpha_0 + \sum_{T=-9}^9 \alpha_{1\#T} NewName_{T_{ct}} + \alpha_2 s_{cptr} + \alpha_3 r_{cpst} + \theta_c + \mu_t + \eta_p + \varepsilon_{cpst} \quad (2)$$

Prior to when a college changes its name, our estimates of  $\alpha_{1\#T}$  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 for

<sup>32</sup>To generate this, we estimate Equation 1 with college rank as the dependent variable and average CEE score as the main explanatory variable. In Figure A.2 we show our estimates of heterogeneity by college rank. We find no evidence of heterogeneity in effects by other dimensions, such as tier or track.

each in which their initial applications to change their names were denied, and the year in which they reapplied and were successful.<sup>33</sup> We generate two estimates of  $\beta_1$  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 which the change was ultimately approved. We report these results in Table A.1. 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 general sign, magnitude, and significance (results shown in Table A.2), suggesting that the college choice of some high-aptitude students was affected by name changes as well as that 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 its average CEE scores, as it would drop those with the lowest scores who would have gained admission were there more slots.<sup>34</sup> 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.3).<sup>35</sup> Fourth, we show that these patterns also appear in individual-level data from

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<sup>33</sup>While 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 November 26, 2020).

<sup>34</sup>In 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.

<sup>35</sup>One potential confounder related to quotas is China’s affirmative action policy for college admission, the “National Special Plan.” This policy provides preferential treatment, via a CEE score “top-up”, to high school graduates in poor regions of the country when they apply to Chinese 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). None of these top universities changed their names during our sample period, 2006-2016. As a result, this affirmative action policy is unlikely to confound our estimation.

Chinese high schools. We present these in Table A.4, 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.

Finally, in Appendix E, we decompose the effect of name changes in terms of the relative gain colleges enjoy by attracting students from competitor colleges and the absolute gain in student quality that comes from attracting students who otherwise would have gone to more selective colleges. Our estimates suggest that roughly 75 percent of the gain is a relative gain, with the other 25 percent coming from an absolute gain, thus construed.

#### *Comparing our results to existing literature*

There are three empirical papers in economics which study a similar phenomenon. The first, Shi et al. (2020), also studies the impact of Chinese college name changes on the ability of institutions to attract more qualified applicants. That study has a much narrower scope than ours in terms of both data and research questions. First, it uses a different and smaller dataset - 552 institutions, as compared to the 1,198 that we study - from a different source, covering roughly the same period.<sup>36</sup> Second, while that study generates overall effect estimates, it does not engage with the broader ecosystem of economic and social questions we analyze: the role of (mis)information in driving effects, characterizing student beliefs about name changes using text data, the effects of name changes on labor market performance, and characterizing employer beliefs.

We can compare that study's main effects to ours; since its main analysis does not standardize the test score outcomes, we primarily comment on the differences in the signs and significance of the relevant estimates in our paper and in it. That study finds no evidence of an overall effect of college name changes, but a significant effect for colleges whose name changes include the shift from college to university, and for those which contain other appealing changes (similar to those we study in the next section). We believe that our findings diverge because we capture the effects on nearly the entire market (we study 1,198 of China's 1,265 BA granting institutions), while that study uses a much smaller sample (only 522 institutions). This likely leads to the difference in

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<sup>36</sup>Its data cover 2005–2015, while ours cover 2006–2016.

overall estimates: the larger sample we use allows us to show how even lower-ranked colleges (particularly, those whose name changes do not include the change from college to university) can and do benefit from name changes.

Two recent studies from the US also target different facets of this phenomenon. 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 (2021) studies how revenue and the *number* of recruited undergraduate and graduate students vary before and after a name change among colleges in the US. In our study, we instead focus primarily on how the *aptitude* of recruited students responds to different types of name change, and whether this is good, bad, or neutral for the careers of students whose choice of college is affected by the name change.

### **3.4 The importance of (mis)information**

As described in Section 2.5, an important dimension of college choice is the information contained in the signals sent by colleges, and how applicants parse these signals. In this section, we study two phenomena that reveal the importance of (mis)information in generating the estimates presented in the previous subsection. First, we generate estimates for two sets of name changes in which the signal sent is either misinformative or contains no information about the college's resources. Second, we show how the magnitude of our overall estimates presented in Section 3.3, as well as these new estimates, vary with the information applicants have about the college.

In Table 3, we present two sets of estimates of the effects of misinformative name changes on college choice. In Panel A, we estimate heterogeneity in the main effect ( $\beta_1$  from Equation 1) across whether the name change includes misleading information about the geographic location of the college. Specifically, 45 name-changing colleges include wording in their new names which suggests that the college is at a province- or national-level (one type of change that would be categorized as type 2 in Table 1), implying that the college would be located in a provincial capital



despite the fact the college is, in reality, located in a city other than the provincial capital. This practice is so misleading that it has been banned by the government in recent years.<sup>37</sup>

We find that these alluring but misleading name changes—a change in signal without a change in fundamentals—have a much larger effect on CEE scores than other types of name changes; our point estimate for the effect of misleading name changes on CEE scores of enrolled students (column 1 of Panel A) is nearly twice the magnitude of that for all other changes (column 2). Furthermore, 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 where the change was initiated by a third party and sends a similarly misinformative signal. As mentioned in Section 2.2, China’s college system contains public and private colleges. Private colleges are generally less selective than public colleges and many private colleges pay for the privilege of affiliation with a parent public college. For example, the private college associated with the University of Science and Technology Beijing is the “University of Science and Technology Beijing - Tianjin College” (in Chinese: *Beijing Keji Daxue - Tianjin Xueyuan*). These colleges experience two types of name changes, both of which occur due to events external to the college. In the first type, the parent public college changes its name, changing the name of the private college in the process. For example, when the Hubei Normal College changed its name to the Hubei Normal University in 2016 its associated private college, Hubei Normal College – Wenli College, changed its name accordingly (becoming Hubei Normal University – Wenli College). These private colleges are not involved in the process of the parent college applying for a name change and there are no requirements applied to them in evaluating the parent college’s name change application. The second type of name change occurs when the government decides the private college must remove the link to the parent college in its name. This occurred in 2016 when the Anhui Polytechnic University – College of Mechanical & Electrical Engineering (*Anhui Gongcheng Daxue – Jidian Xueyuan*) was made to sever its link to its parent college, changing its name to be the Anhui College

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<sup>37</sup>One relevant policy that regulates this type of name change is “A temporary regulation on naming colleges” (available at [http://www.gov.cn/zhengce/zhengceku/2020-08/31/content\\_5538872.htm](http://www.gov.cn/zhengce/zhengceku/2020-08/31/content_5538872.htm); accessed July 21, 2021). This regulation specifically prohibits the type of misleading geographical names we study here.

of Information Technology (*Anhui Xinxi Gongcheng Xueyuan*). In this case the government may also require an increase in facilities or other investment at the college.

The impact of these misinformative name changes on enrollment highlights the role of (mis)information in driving our effects. The first change sends a positive signal with no change in fundamentals, while the second may send a negative signal despite a possible positive change in fundamentals. Our results in column 1 of Panel B show a large, positive effect for private colleges whose parent college upgrades its name, despite there being no contemporaneous changes whatsoever at the private college that corresponds to the parent's name change. In column 2, we estimate negative effects for private colleges severing ties to their parent colleges. These losses occur despite the effect that these colleges sometimes are required to increase their resources. This shows even more clearly the signaling value of college names, separate from the information about resources contained in that name.

Next, we analyze a related question - how do the effects of college name changes vary with the information applicants have about the college. In these analyses, we estimate effects for students from within the same province in which the college is located, and compare them to the effect among students from outside of the province. Following Loyalka et al. (2016) 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.

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 shows two key patterns. 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, while for within-province students the two are not statistically distinguishable. These patterns are consistent with out-of-province applicants being less familiar with the institution to begin with—and thus more likely to be influenced by the new name—than students applying from within the same province.<sup>38</sup>

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<sup>38</sup>We 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

Table 3: The impact of unambiguously misinformative name changes

<i>Panel A: Name change includes alluring but misleading geographic information</i>		
	(1) New name is alluring but misleading	(2) All other name changes
Effect on average CEE score (in SD units)	0.084*** (0.007)	0.048*** (0.004)
Colleges that changed names	45	199
Colleges in sample	1,198	1,198
Number of observations	418,441	418,441
<i>Panel B: Private college name changes where signal indicates incorrect quality change</i>		
	(1) Uses parent college's new name	(2) Drops link to parent college
Effect on average CEE score (in SD units)	0.088*** (0.008)	-0.014* (0.008)
Colleges that changed names	60	56
Colleges in sample	1,198	1,198
Number of observations	418,441	418,441

Note: this table shows how our estimates of the effect of name changes vary by whether the name change contains misinformation. 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 schools whose “parent” public institutions change their name, separately for whether or not the private school is allowed to keep the new name. In both panels, the row entitled “Effect on average CEE score” reports the results for estimating  $\beta_1$  in Equation 1 for the group named in the column heading. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

In Panels B and C of Table 4, we show how the estimates of the effects of misinformative name changes presented in Table 3 vary by students' baseline knowledge about the college. In these estimates too, we measure much larger responses to the signal of a name change (in these cases, when it is misinformative) among out-of-province applicants than among within-province applicants. We also measure larger differentials between misleading and non-misleading changes among out-of-province students.

Together, these results show that misinformation and access to information play a large role in driving the effects of college name changes on college choice. We see larger effects when the name changes contain alluring but misleading signals. We also find that the sign of these effects depends on whether the name change sends a positive or negative signal, despite the fact that in both cases the signal is entirely uninformative. Finally, we see that all of these effects are larger when students are less informed about the college whose name changes.

### **3.5 Student beliefs about and experience of college name changes**

In this subsection we report analysis of text scraped from a major website containing online discussions regarding the phenomenon of college name changes. These text data contain accounts of students' beliefs about and experience of these name changes. We have two goals for analysis of these data. The first is to more richly characterize what students perceive about college name changes and how this may influence college choice. The second is to further scrutinize our interpretation of the results presented so far in this section: that college name changes are successful in attracting higher-aptitude students partly because students have imperfect information about college quality, allowing cosmetic features of new names to sway their decisions even when these features convey little (or misleading) information.

We analyze text data scraped from the website [www.zhihu.com](http://www.zhihu.com), the largest Q&A platform in China. The site's format is similar to the popular website [quora.com](http://quora.com), where questions are posted in an environment with more people and more flow of information than colleges located in smaller cities. We show these results in Table A.5; 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.

Table 4: Heterogeneity of 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)
Colleges that changed names	244	109	232	104
Colleges in sample	1,183	1,183	1,183	1,183
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)
Colleges that changed names	45	199	44	188
Colleges in sample	1,183	1,183	1,183	1,183
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)
Colleges that changed names	60	56	57	52
Colleges in sample	1,183	1,183	1,183	1,183
Number of observations	393,292	393,292	25,139	25,139

Note: this table shows estimates of  $\beta_1$  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. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

and users can post responses. 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 discuss the details of data collection and several additional analyses in Appendix F.

In these data, many students report making college choice under imperfect information. Many others report being impressed or influenced by college name changes. These discussions also contain several entries from people reporting they were misled by such changes when making their choice of college. Dozens of comments allege that such effects are most likely to occur among out-of-province applicants, a subgroup among whom we showed larger effects of college name changes in Table 4.

Our interpretation of these data is that such problems of inference occur for students who choose to attend a wide variety of colleges. There were 226 unique schools whose name changes were discussed in these threads. As would be the case in analyzing data from US Q&A sites such as quora.com, our analysis of zhihu.com 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 (some) applicants to hundreds of China's BA-granting institutions, all of which had changed their names. Our statistical analysis of these data yields the following additional findings:

*Misinformation and the information gap was the most frequent topic discussed.* We searched for keywords related to five topics (described in Table A.9); among these, keywords related to information were the most popular, appearing in 11.2 percent of the 3,000 discussions. Analysis of the discussions related to this reveals several phenomena which corroborate our original results, including: i) students from outside of the province in which a college is located were more likely to be “cheated” or “fooled” by name changes; ii) some students reported incorrectly inferring the

location of the college from its name (as analyzed in Panel A of Table 3); and iii) others reported applying to private colleges because of their affiliation with a famous parent college.

*The most popular discussions were related to i) changes from college to university and ii) private colleges whose name change severed ties to the parent public college.* Both of these name change types had roughly 20 percent more comments and “likes” than other types.<sup>39</sup>

*The sentiment around these two topics points in opposite directions.* The sentiment in discussions about changes from college to university was generally positive and associated with putative success in raising CEE scores. The sentiment in discussions surrounding private colleges whose name change severed ties to the parent public college, on the other hand, was highly negative.

*There was far less discussion of college resource changes or the impact of name changes on employment.* We were surprised to find far fewer discussions which discussed keywords related to the resources at a college changing with the name change (1.9 percent of discussions) or the impact of name changes on employment (1.1 percent).

To conclude this section, in Table 5 we provide eight vignettes from these discussions. These vignettes illustrate the messages described above, showing how students’ beliefs and the (mis)information they have about college name changes are seen to influence college choice. These corroborate our interpretation that uncertainty and misinformation are key drivers of the estimates we present in earlier subsections.

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<sup>39</sup>These analyses, and the results below, are presented in Table A.10 in Appendix F.

Table 5: 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 University, 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>
Name changes likely to influence 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](http://www.zhihu.com) and that we analyze in this section.



## 4 How college name changes affect labor market performance

The changes in behavior induced by college name changes could be either good, bad, or neutral for the labor market outcomes of affected students after graduation. In this section, we assess this by analyzing data from a large resume audit study, administrative data from China’s civil service exam, and data from a survey of HR professionals.

### 4.1 Research design of resume audit study

In the resume audit study, we wish to understand whether there is a premium for applicants listing a college’s new name, relative to its old name. We also estimate i) whether, in lower-paying and lower-status jobs, there exists a penalty for listing a new college name, perhaps as a result of employers perceiving these applicants as over-qualified for these jobs, and ii) whether there exist patterns of heterogeneity related to the employer’s geographic distance to the college similar to those we observed among college applicants.

Several aspects of the Chinese labor market facilitate this resume audit study. First, China has the world’s largest labor market. As of 2018, there were 775.9 million people officially employed according to government records (Ministry of Human Resources and Social Security of the People’s Republic of China, 2019a). Second, the vast majority of employees work in private firms; since 2012, more than 80% of Chinese workers have been employed in the private sector (Li et al., 2012). Finally, much of the search for these jobs occurs via the internet: according to government statistics, approximately 76 percent of job openings are currently posted online (Ministry of Human Resources and Social Security of the People’s Republic of China, 2019b).

Our design follows that of recent resume audit studies investigating the value of for-profit colleges (Darolia et al., 2015; Deming et al., 2016) and the extent of race-based discrimination in the labor market (Agan and Starr, 2017). We sent over 14,000 fictitious resumes to employers across six cities in China between November 2018 and November 2019. We used two job posting websites in China – *www.51job.com* and *www.zhaopin.com* – as our main sources for job advertise-

ments. These are the two largest job sites in China<sup>40</sup> and have been used in other studies on China's labor market (Kuhn and Shen, 2013). Our resumes varied on the following five key dimensions:

*Old college name vs. new college name.* Our main dimension of variation is whether the resume listed a college's old name or its new name. We used only colleges whose name change was from college to university.<sup>41</sup>

*City of job posting.* We submitted resumes to jobs in six cities – Hangzhou, Hefei, Shanghai, Wuhan, Xi'an, and Zhengzhou. We chose these because i) the provinces they are located in each had two colleges which changed their names to university in the last five years, allowing for our resumes to plausibly list either the old or new name<sup>42</sup>; ii) they are large cities with robust labor markets; and iii) they are representative of mainland China's three main geographic regions.<sup>43</sup>

*Industry.* We submitted resumes to jobs in the following two industries: computer programming and human resources/administration (in Chinese, *xing zheng*).<sup>44</sup> These two job types were among the top six occupations in terms of number of posted jobs and top three in terms of number of job applicants in the fall of 2018.<sup>45</sup>

*Work experience.* We focused on jobs that asked for up to two years, or three to five years

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<sup>40</sup>According to [https://www.sohu.com/a/155316030\\_182188](https://www.sohu.com/a/155316030_182188), accessed January 2, 2019

<sup>41</sup>We also used only colleges which allow us to plausibly list either the new or old name based on date of enrollment and 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. The full list of colleges, with their old name, new name, and date of name change, are given in Table A.6. Using the CEE data described in Section 3, we estimate the impact of these colleges' name changes on CEE scores to be a roughly 0.07 SD increase, well within the confidence interval of our estimated effect of college-to-university name changes on CEE scores reported in column 2 of Table 2.

<sup>42</sup>We chose to list colleges that changed names around the year of the fictional students' graduation so that listing the new name or old name would both be plausible. Note that the callback rates we study make up the first round of a longer recruitment process. As such, we expect the HR professionals whose callbacks we record will have examined hundreds of resumes each day. As a result, we argue that it is unlikely for them 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. Furthermore, we observe this pattern in the civil servants data discussed in Appendix G; specifically, we observe hundreds of cases 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.

<sup>43</sup>Eastern region: Shanghai, Zhengzhou. Central region: Hangzhou, Hefei, Wuhan. Western region: Xi'an.

<sup>44</sup>Deming 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.

<sup>45</sup>According to <https://www.hroot.com/detail.aspx?id=9383823>, accessed January 15, 2019.

of experience, respectively; the resumes we submitted listed the appropriate number of years of experience for each job type.

*Location relative to job posting.* We varied whether the college listed is in the same province as the job being applied to, or in the province of one of the other five study cities.

Each resume lists the name, email address, phone number, work experience, skills, and simple biographical information for the applicant. We created resumes using realistic applicant characteristics based on publicly available resumes posted on those two job sites.<sup>46</sup> Before finalizing the resumes to be used in the study, each resume was vetted by a team of three HR professionals to ensure its appropriateness for that type of job posting.

We created pairs of resumes within each city–experience–industry–relative location–college cell – one listing the old name, the other listing the new name. In total, this gave us 192 resumes. We submitted one resume pair to each job, following the example of previous resume audit studies (e.g., Deming et al., 2016). We contracted a team of four human resources / hiring professionals to vet each cell of resumes for two concerns: one, that a given resume was inconsistent or not believable, and two, that the two resumes within each cell were similarly desirable from the perspective of the employer.<sup>47</sup>

Applicant 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 given required experience level (two years or 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.

Our main outcome variable is the rate at which resumes received callbacks. Our initial sample

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<sup>46</sup>Specifically, we 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.

<sup>47</sup>Due 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.

Table 6: Summary statistics for resume audit study

<i>Job type</i>	(1) Received callback	(2) Number of observations
Overall	0.136	14,152
Two years of experience	0.141	7,412
Five years of experience	0.131	6,740
Local	0.139	6,990
Non-local	0.133	7,162
Programming	0.130	7,206
Administration	0.143	6,946

Note: this table shows summary statistics on the rate at which resumes received callbacks, and the number of observations, across the main dimensions of heterogeneity in our resume audit study.

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 percent of the total) because of three types of error: i) more than one pair was submitted to the same posting; ii) 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 iii) the resumes submitted to the job were accidentally from different pairs. We show summary statistics for callback rates by resume type in Table 6. In addition to data on callbacks, we also collected the following data on each job posting: salary, number of employees at the company, minimum required degree, and the type of company (e.g., private company, publicly listed company, and so on).

## 4.2 Analysis methods

Our pre-specified primary outcome is a simple comparison of means: we calculate 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.<sup>48</sup> 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. Subsequent pre-specified secondary analyses use ordinary least squares linear probability regressions, using the old name as the baseline case, and adding controls for job type, experience level, and whether or not the resume lists a college from a local area or a non-local area. Our main specification is:

$$y_{ije} = \gamma_0 + \gamma_1 \text{NewName}_{ije} + \vartheta_j + \delta_e + \zeta_l + \varepsilon_{ije} \quad (3)$$

Here  $y_{ije}$  is an indicator for whether resume  $i$  in job type  $j$  (admin or programming) in experience level  $e$  (either “two years or less” or “three to five years”) receives a callback.  $\vartheta_j$ ,  $\delta_e$ , and  $\zeta_l$  are fixed effects for the job type, experience level, and whether the college is local to the job being applied to, respectively and  $\varepsilon_{ije}$  is an error term at the resume level.

We also estimate whether the old name/new name callback differential varies across industries, between resumes listing two years of experience and those listing five, and between resumes listing local colleges and those listing non-local colleges.<sup>49</sup> To follow Deming et al. (2016), we also display a slightly different format of these regressions, estimating the equation separately by job type, experience, and local/non-local status.

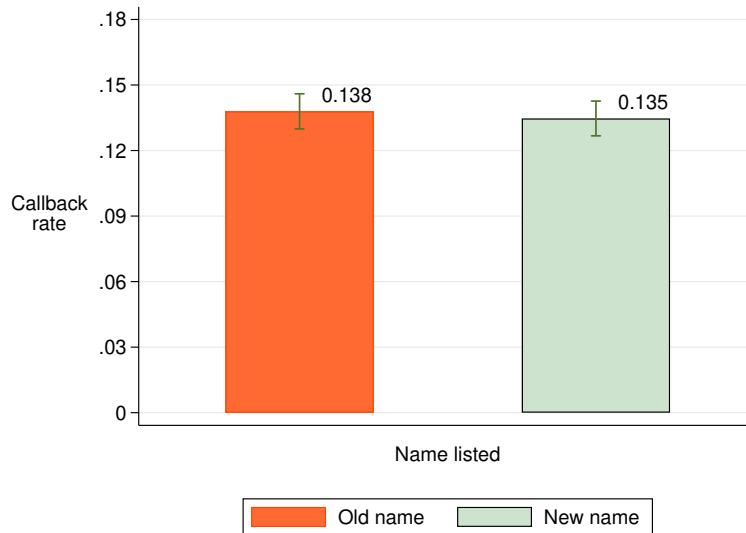
### 4.3 Main audit study results

We show mean callback rates for resumes listing old college names and new college names, respectively, with the associated confidence intervals, in Figure 3. The overall callback rate is roughly 13.6 percent, and the difference in means is 0.325 percentage points. We are unable to reject our null that the callback rates were the same for the two types of resume (the p-value for the comparison of means is 0.573). The confidence intervals we generate exclude anything larger than a 1.46

<sup>48</sup>We wrote and registered a pre-analysis plan for this part of our study. Available at [socialscienceregistry.org/AEARCTR-0003669](https://socialscienceregistry.org/AEARCTR-0003669).

<sup>49</sup>Equivalently, between those that changed their names more recently (2016 or after) compared with colleges that changed their name less recently (between 2012 and 2015).

Figure 3: Overall difference in callback rates



Note: this figure shows the callback rate for all resumes, separately by whether the resume listed the college’s old name (orange) or new name (green), along with confidence intervals of the estimate of the callback rate. The p-value for a test of the null of equality between the estimated callback rate for the two groups is 0.573.

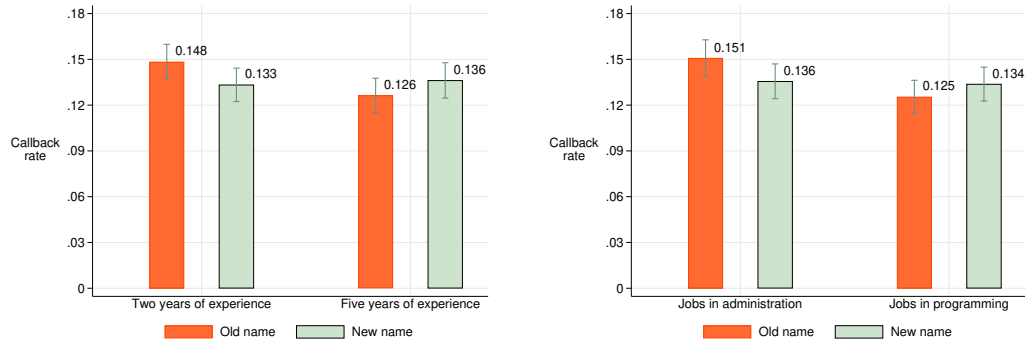
percentage point difference.<sup>50</sup>

In Figure 4 we report pre-specified subgroup analysis in old name/new name callback rates. In Panel A we show the callback rates for old name and new name resumes listing two years of experience in the left two bars, and for those listing five years of experience in the right two bars. Among resumes with two years of experience, the callback rate for those listing the college’s old name is 1.51 percentage points higher than for those listing the new name, though this difference is only marginally statistically significant at traditional levels (p-value = 0.062). Among resumes with five years of experience, the callback rate for those listing the college’s old name is 0.98 percentage points lower than for those listing the new name, but this difference is also not statistically significant (p-value = 0.234).<sup>51</sup> In Panel B we show the old name/new name callback differential

<sup>50</sup>For reference, our study design powered us to detect a minimum difference of 1.15 percentage points in callback rates, from a baseline of 10 percent of old name resumes receiving callbacks.

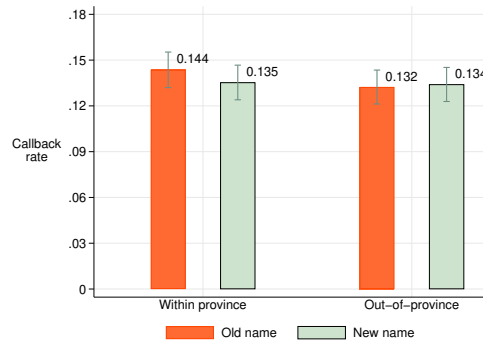
<sup>51</sup>Note that experience is collinear with time elapsed since the college changed its name; the diffusion of information over time may also generate a difference in old name/new name callback rates. We anticipate both effects to push in the same direction: as time elapses, we expect less of 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,

Figure 4: Callback rates by subgroup



Panel A: Difference in callbacks by experience of applicant

Panel B: Difference in callbacks by job type



Panel C: Difference in callbacks by within province vs. out-of-province college

Note: this figure shows the callback rates for resumes listing the old college name (in orange) and the new college name (in green) for three pre-specified dimensions of heterogeneity. Panel A shows this for resumes sent to jobs requiring two or less years of experience vs. those sent to jobs requiring 3-5 years of experience; Panel B shows this for resumes sent to jobs in administration vs. those to jobs in programming; and Panel C shows this for resumes listing colleges within the province of the job posting vs. outside of the province. P-values for these comparisons are given in the text.

across resumes in the two different industries we targeted, administration and programming. For jobs in administration, the callback rate for resumes listing a college's old name is 1.53 percentage points higher than for those listing the college's new name; this difference is again on the margin of statistical significance (p-value = 0.070). The callback rate for resumes submitted to programming jobs listing a college's old name is 0.83 percentage points lower than for those listing the college's new name (p-value = 0.29).

In Panel C we show the within-province and out-of-province callback rates by college name. For within-province resumes, the callback rate for those listing the college's old name is 0.83 percentage points higher than for those listing the new name. The callback rate for out-of-province resumes listing the old name is 0.11 percentage points lower than those listing the new name. Neither difference comes close to statistical significance; we interpret this as evidence that employers may have better (and more uniform) information about the impact of college name changes than college applicants.

We show the regression equivalent of these results in Table 7. We did not pre-specify any further within-group analyses (e.g., within job type, by years of experience or local/non-local). Instead, we present these as non pre-specified, exploratory analyses in the next subsection, along with our interpretation of the patterns we observe.

#### **4.4 Heterogeneity by job type**

In this section, we present analyses which further probe our pre-specified analysis of heterogeneity in callback rates by job type.<sup>52</sup> As discussed in the introduction, one stylized fact emerging from large scale resume audit studies in numerous contexts – including the US, China, and India – is that in some cases there may be a penalty for resumes which list traits that signify applicant quality, relative to resumes which do not (Deming et al., 2016; Chen, 2019; Sekhri, 2020). These penalties arise when the recruiter has reason to believe that the applicant is overqualified for the

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the relative importance of the name of the candidate's college decreases.

<sup>52</sup>These analyses were not pre-specified in our analysis plan. As a result, we see the results in this subsection as primarily hypothesis-forming analyses, rather than analyses testing specific hypotheses.



Table 7: Main audit study results in regression format

<i>Sample</i>	(1) Coefficient on new college name	(2) Old name callback rate	(3) Number of observations
Entire sample	-0.0033 (0.0058)	0.138	14,152
Jobs in programming	0.0083 (0.0078)	0.125	7,206
Jobs in administration	-0.0153* (0.0083)	0.151	6,946
Jobs requiring two years of experience	-0.0151* (0.0080)	0.148	7,412
Jobs requiring five years of experience	0.0098 (0.0081)	0.126	6,740
College in same province as job	-0.0083 (0.0083)	0.144	6,990
College in different province from job	0.0017 (0.0080)	0.132	7,162

Note: this table shows results from regressions of the callback rate on the new college name and additional controls, as in Equation 3, restricting the sample as described in labels given in the leftmost column. We exclude controls for resume types when appropriate, e.g., we exclude the job type control when restricting the sample to only jobs in administration or programming. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table 8: Heterogeneity in new name callback premium by job type

	<i>Jobs in administration</i>		<i>Jobs in programming</i>	
	(1)	(2)	(3)	(4)
	Two years of experience	Five years of experience	Two years of experience	Five years of experience
$\alpha$ : New name callback rate – minus old name callback rate	-0.033***	0.007	0.005	0.012
$\alpha$ 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: the first line of each cell in this table shows the parameter  $\alpha$ , defined as {[new name callback rate] - [old name callback rate]}. The second line shows this difference as a percentage of the old name callback rate for that cell. The third line, in brackets, shows the p-value for a t-test of the null: new name callback rate = old name callback rate. \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

job, the downside of which is difficulty in recruiting and retaining the applicant, as well as potential under-performance in the job due to dissatisfaction. In such situations, the recruiter may privilege resumes without these traits in order to avoid wasting resources on an applicant who would not be a good fit for the job in question.

In this section, we explore the possibility of this type of “heterogeneity by match quality.” We first present this by breaking the new name/old name callback rate comparison into four cells, across the four possible combinations of job type (administration or programming) and experience level (two years required or five years required). We present these results in Table 8. In this table, we show estimates of the difference in callbacks between resumes listing a college’s new name and resumes listing its old name, a parameter we call  $\alpha$ . In addition to  $\alpha$  itself, we also show  $\alpha$  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  $\alpha = 0$ .

For jobs in administration, this analysis reveals heterogeneity in  $\alpha$  by experience level. For jobs requiring two years of experience, resumes listing a college’s old name are 3.3 percentage points

(15.4 percent) more likely to receive a callback than similar resumes listing the college's new name. This difference is highly significant, with a p-value of 0.010.<sup>53</sup> This is precisely the cell where we expect the greatest risk of mismatch, as administration jobs are potentially lower status and certainly less well-paid than programming jobs, and jobs requiring two years of experience are less well-paid than jobs requiring five years. In all other jobs, we see a 6-10% benefit for listing a college's new name, relative to its old name, though these differences are not statistically significant.

To further probe the relationship between potential mismatch and a penalty for listing a college's new name, we conduct a series of exploratory analyses within this category of jobs: administrative jobs requiring two years of experience or less. We use regression analysis, as described in Section 4.2, to estimate potential heterogeneity across five dimensions: the type of firm (private vs. public or listed firms); the size of the firm (less than 500 employees vs 500 or more); the college ranking of the college listed in the resume (above or below the median ranking of the colleges we used); the salary listed on the job advertisement (above or below the median); and whether the minimum credential required is an associate's or bachelor's degree.

We show our results in Table 9. In all cases, we see a higher new name penalty where there is a larger risk of mismatch. For firm characteristics, we see a larger new name penalty among private firms and, separately, smaller firms, both cases where there is larger proportional risk of hiring one employee who is a bad match (assuming that a larger or wealthier firm would be better able to absorb that risk). For applicant type, we see a much larger new name penalty for applicants coming from higher-ranked colleges. Overall, the results are consistent with the general patterns we would expect from recruiters trying to avoid recruiting over-qualified applicants to these jobs.

These results are consistent with the over-qualification story described in Chen (2019) and Sekhri (2020). Chen (2019) uses a resume audit study to compare the appeal of applicants to jobs in China based on whether their BA was from a US- or China-based college. That study finds a penalty for applicants listing US-based colleges – particularly at jobs with lower salary or other

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<sup>53</sup>This 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.

requirements – interpreting 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.

One alternative possibility for the new name penalty for these jobs is that employers for them are unfamiliar with the new names and, because recruitment for a lower-paying job has lower financial stakes for the company than for a higher paying job, do not bother to look them up. While this is possible – and consistent with one of the other potential interpretations suggested by Chen (2019) – we present evidence in the next section that this is less likely than the over-qualification story. Specifically, we show that employers observe the aptitude difference between graduates from the same college listing old names vs. those listing new names. Furthermore, surveyed hiring professionals attest to being familiar with these name changes and believing that name changes attract better students.

#### **4.5 Employer beliefs about and experience of college name changes**

In this section, as in Section 3.5, we analyze data which contains information on the beliefs of people affected by these changes. In this case, we wish to know what HR professionals observe and believe about graduates of name-changing colleges. We report analysis of two datasets: first, administrative data from China’s civil service examination which shows the observable aptitude of candidates listing a given college’s old and new name. Second, we analyze responses to an online survey of HR professionals we conducted to better understand employers’ subjective beliefs of this phenomenon.

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 aptitude. Specifically, in this data we see that applicants who graduate from a college after the name change earn 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 many recruiters

Table 9: 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
	Large, public 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	-0.034** (0.016)	0.213	2,583
	Above median	-0.030 (0.021)	0.202	1,329
<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 coefficient estimates from regressing the callback rate on an indicator for the resume listing the college's new name, restricting the sample to those jobs in administration requiring two or fewer years of experience, and fitting 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. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

likely observe the difference in student aptitude associated with college name changes that we measure in Section 3. We present further analysis of these data in Appendix G.

Finally, we analyze data from an online survey of 87 HR professionals who were 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, however, 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.<sup>54</sup>

Further reflecting our interpretation of the resume audit study results, respondents whose main responsibility was hiring candidates in administration (i.e., lower paying jobs with lower skill requirements) were either indifferent between the applicants listing college (the old name) or university (the new name) in a given college's name, or actually preferred applicants listing college (the old name). Respondents hiring primarily in programming, on the other hand, reported strict preference for candidates listing university (the new name). Appendix H contains further details.

## 5 Conclusion

Using administrative and experimental data from China, we study how college efforts to improve their reputation through changing their names affects college choice and the labor market performance of recent college graduates. The first main take-away from our study is that these name changes generate real increases in the quality of the college, as measured by the aptitude of the students it recruits. This occurs even when the new, more appealing name contains no other information about fundamental traits of the institution. The fact that we see larger effects from

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<sup>54</sup>The 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.

appealing but misinformative name changes, and larger effects among students with less information about the institution, highlights the role of misinformation in generating these outcomes. This is also reflected in our analysis of text data from online discussion boards in China, in which we find many students who report being misled by college name changes.

These college name changes could either help or harm the labor market performance of college graduates. 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 jobs where candidates listing the new college name may appear overqualified, and positive but statistically insignificant impacts in other jobs. Our analysis of administrative civil service data and survey data from employers guide our interpretation of these patterns. We see that people who hire recent college graduates observe and are aware of the fact that name-changing colleges attract higher-aptitude students, and say that they respond accordingly.

As a whole, our study highlights a key feature of markets with imperfect information. Even in “high stakes” markets such as those we study, signals designed to change participants’ beliefs – including those which are entirely uninformative or even misinformative – can generate real, self-fulfilling, and self-perpetuating processes.

## References

- Acton, Riley**, “Is a name change a game change? The impact of college-to-university conversions,” *EdWorkingPaper Number 21-417*, 2021.
- Agan, Amanda and Sonja Starr**, “Ban the box, criminal records, and racial discrimination: A field experiment,” *Quarterly Journal of Economics*, 2017, *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 uncertain,” *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.
- 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. URL: <https://www.bostonglobe.com/metro/2017/08/09/same-schools-new-names/CxQrzW5Ih5q9BoIkRWRoRO/story.html>, accessed October 13, 2020.
- 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.
- 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.

- Clark, Kim**, “Colleges play the name game,” *US News and World Report*, September 17 2009. URL: <https://www.usnews.com/education/articles/2009/09/17/colleges-play-the-name-game>, accessed October 13, 2020.
- Clinton, Kirsten**, “What’s in a name? The signaling value of university education,” *Working Paper*, 2020.
- 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. <https://www.nytimes.com/2005/08/11/education/to-woo-students-colleges-choose-names-that-sell.html>.

**Goodman-Bacon, Andrew**, “Difference-in-differences with variation in treatment timing,” *Journal of Econometrics*, 2021.

**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.

— **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**, “Do poor, rural students make inefficient college and major choices? Evidence from China,” *Working Paper*, 2016.

**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.

**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.

**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/buneiyaowen/201905/t20190524\\_318428.html](http://www.mohrss.gov.cn/SYrlzyhshbzb/dongtaixinwen/buneiyaowen/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/t20190611320429.html](http://www.mohrss.gov.cn/SYrlzyhshbzb/zwgk/szrs/tjgb/201906/t20190611320429.html).

**Mulhern, Christine**, “Changing college choices with personalized admissions information at scale: Evidence on Naviance,” *Journal of Labor Economics*, 2021, 39, 219–262.

**Newlon, Cara**, “The college amenities arms race,” *Forbes*, July 31 2014. URL: <https://www.forbes.com/sites/caranewlon/2014/07/31/the-college-amenities-arms-race/>, accessed February 20, 2020.

**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, pp. 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 non-profit college and university mergers,” *Review of Economics and Statistics*, 2019, pp. 1–45.

**Sacerdote, Bruce et al.**, “Peer effects in education: How might they work, how big are they and how much do we know thus far,” *Handbook of the Economics of Education*, 2011, 3 (3), 249–277.

- 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,” *The 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*, 2020.
- 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. URL: <https://www.chronicle.com/article/whats-in-a-name-letters-and-lots-of-em/>, accessed October 13 2020.
- 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, pp. 133–154.
- Winter, Greg**, “Jacuzzi U.? A battle of perks to lure students,” *New York Times*, October 5 2003. <https://www.nytimes.com/2003/10/05/us/jacuzzi-u-a-battle-of-perks-to-lure-students.html>.
- Wong, Alia**, “What’s the difference between a college and a university?,” *The Atlantic*, November 19 2019. URL: <https://www.theatlantic.com/education/archive/2019/11/is-a-college-different-from-a-university/602215/>, accessed February 29, 2020.

**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.

## Appendix tables and figure

Table A.1: 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)
Number of colleges that changed names	9	9
Total number of colleges in sample	1,198	1,198
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 names were 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  $\beta_1$  in Equation 1 for the group named in the column heading. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



Table A.2: 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)
Number of colleges that changed names	244	109
Total number of colleges in sample	1,198	1,198
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  $\beta_1$  in Equation 1 for the group named in the column heading. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table A.3: 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)
Number of colleges that changed names	80	69
Total number of colleges in sample	673	673
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)
Number of colleges that changed names	80	69
Total number of colleges in sample	673	673
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  $\beta_1$  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.4: 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)
Colleges that changed names	53	40
Colleges in sample	453	453
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  $Score_{ispct} = \mu_0 + \mu_1 NewName_{ct} + \mu_2 X_i + \mu_3 Private_s + \mu_4 Tier_{ct} + \phi_c + \varphi_p + \psi_t + \varepsilon_{ispct}$ , 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  $\phi_c$ ,  $\varphi_p$ , and  $\psi_t$ , 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 can use it to estimate whether the average scores of children going to a given school increase when the school changes its name, akin to columns 1 and 2 of Table 2. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table A.5: 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)
Colleges that changed names	163	79	81	30
Colleges in sample	763	763	435	435
Number of observations	275,819	275,819	142,622	142,622

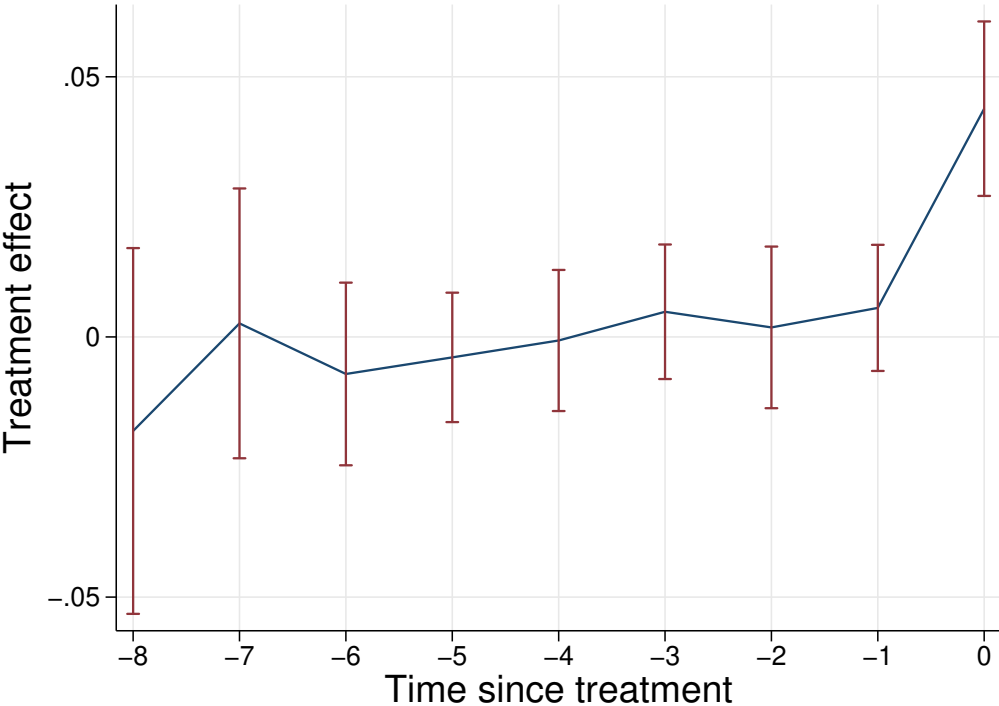
Note: in this table, we compare effects for name changing colleges located in large cities (columns 1 and 2) to those for small and medium-sized cities (columns 3 and 4). The row entitled “Effect on average CEE score” reports the results for estimating  $\beta_1$  in Equation 1 for the group named in the column heading. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

Table A.6: 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 (Teacher's) 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

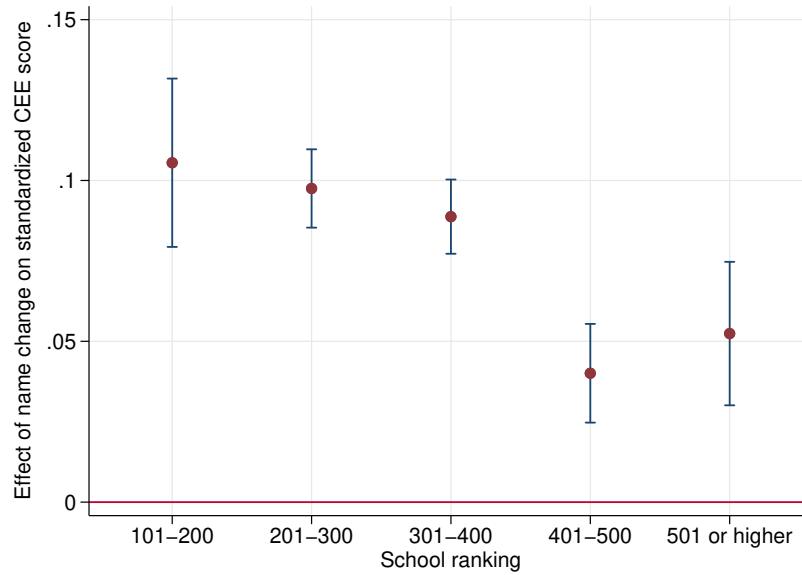
Note: This table lists the old name, new name, and year of name change for colleges used in the resume audit study. For each college, the name in English is given in the first row, and the name in Chinese is given below in italics. The capital city of the province is where the job postings to which we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

Figure A.1: Parallel trends test from de Chaisemartin and d’Haultfoeuille (2020)



Note: this figure shows placebo estimates from the command *did\_multiplot* 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.2: Heterogeneity in the effect of name changes on CEE scores by baseline college rank



Note: this figure shows the coefficient  $\beta_1$  and corresponding confidence interval estimated from 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 ranking of treated colleges (no treated colleges are ranked 100 or higher).

# Supplementary appendix - for online publication

## 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, 2021). In 2015, an Associated Press 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 (2021), 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, for most colleges 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, it 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 percent 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 Feb 23, 2020.*

## C How academic resources and scholarly output vary with 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 vary with a change in name, using data 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 regarding the college’s research funding and output, spanning from 2007 to 2016. These data include the amount of research funding under management by the college, the number of faculty members in the sciences (excluding those in arts, humanities, social sciences, and other non-science departments) working at the college, the number of scientific projects at the college funded by the national government, and the number of academic papers published faculty members there. We gathered these data from the College Science Statistical Yearbooks (*gaodeng xuexiao keji tongji ziliao huibian*) published by the Chinese Ministry of Education.

The main resource-related outcomes we study pertain to the annual scientific output of the university and its faculty strength. The resource variables include the number of government funded projects it has, the number of elite government research awards it has, the amount of government funding under management, and the number of papers published by scholars at the university. We also observe the number of faculty members at the college.

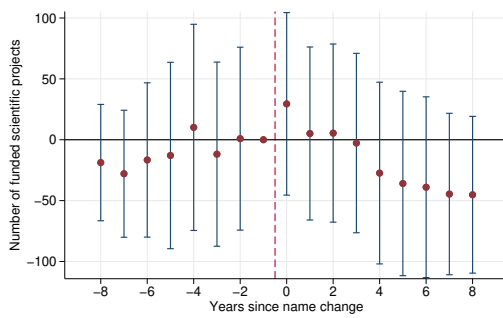
To study this relationship, we estimate a version of equation 2,

$$y_{cpstr} = \delta_0 + \sum_{T=-9}^9 \delta_{1\#T} NewName_{Tct} + \theta_{es,c} + \mu_{es,t} + \varepsilon_{cpst} \quad (4)$$

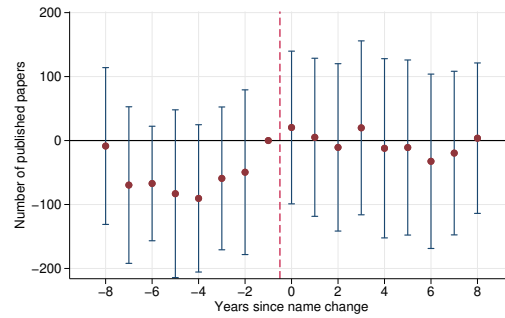
We use outcome variables at the college-by-year level; as a result, we control for only college

$(\theta_{es,c})$  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 A.3 in a manner parallel to Figure 2. We see that scientific funding and 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 changes about these universities in the year of a name change. In Table A.7, 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.

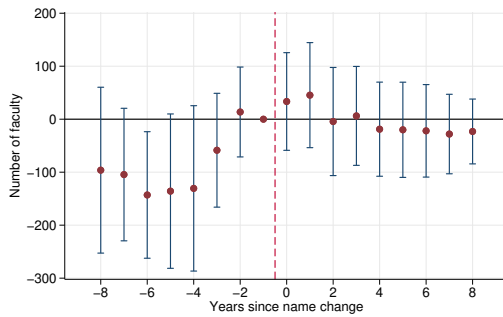
Figure A.3: How resources change with college name changes



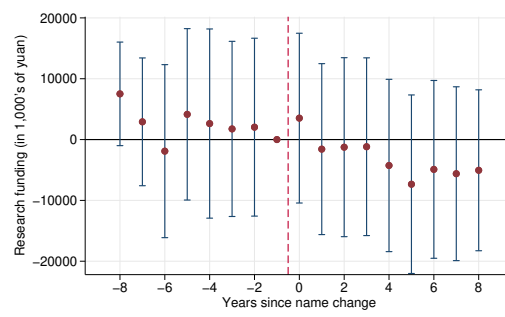
*Panel A: Number of scientific projects*



*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 2, only showing the estimated impact of college name changes on the college resources described in the panel title and the y-axis of the figure.

Table A.7: Main effects, 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)
Number of colleges that changed names	175	97
Total number of colleges in sample	954	954
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)
Number of colleges that changed names	175	97
Total number of colleges in sample	954	954
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, but using only colleges in the sample for whom we have resources data, that is, annual data on the number of federal projects, the amount of research funding currently under management by the college, and the number of papers published. Panel B shows a specification similar to Table 2 and Panel A of this table, but estimated including these three “resource” variables as controls on the right hand side of Equation 1. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

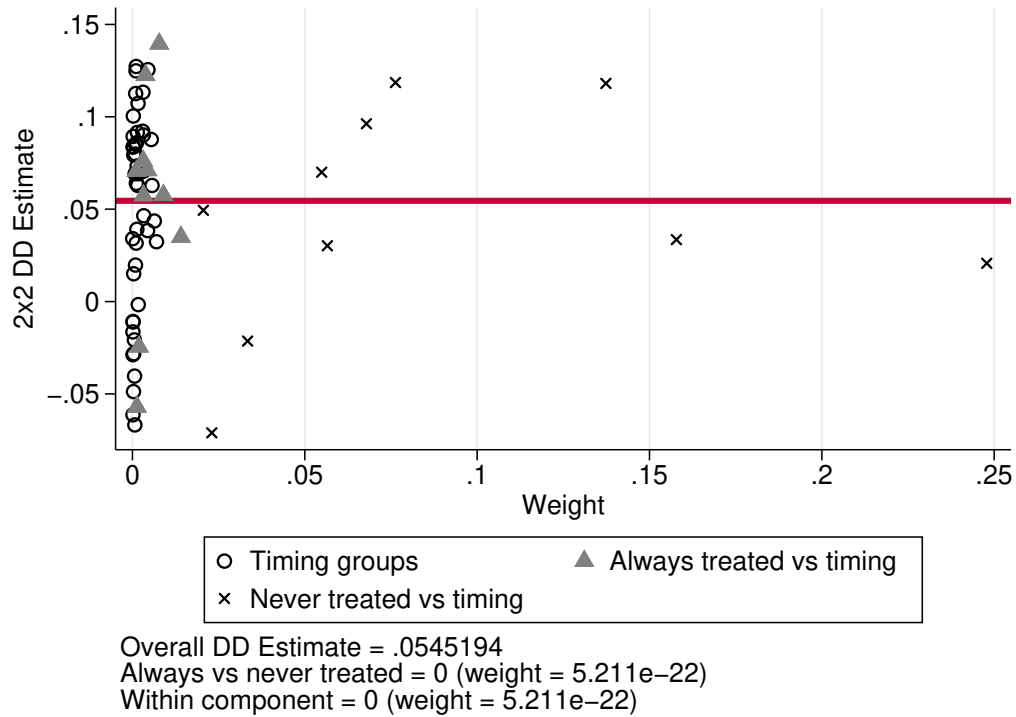
## D Testing for negative weights in ATE estimates from our DiD strategy

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 estimands: 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; Sun and Abraham, 2020; Goodman-Bacon, 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 A.4, 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.1, 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



Figure A.4: Estimates and weights of our DiD 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.

Table 2, we find positive and statistically significant estimates which vary slightly in magnitude 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  $\beta_1 = 0.0570$ ,  $se = 0.00928$ . 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 Disentangling absolute and relative gains from college name changes**

Each year, colleges compete for students. As a result, a large component of our estimates may come from the college attracting students who would have otherwise attended another competitor college. We attempt to separate this relative gain from the absolute gain in student quality by restricting the comparison (or “untreated”) group to two alternative control groups unlikely 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.<sup>55</sup> 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 A.8. 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 0.015-0.02 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 the absolute gain, 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

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<sup>55</sup>In 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 A.8: Using elite colleges only as the control group

<i>Panel A: Elite 211 universities as comparison group</i>		
	(1)	(2)
	All name changes	College to university
Effect on average CEE score (in SD units)	0.015*** (0.004)	0.020*** (0.005)
Colleges that changed names	244	109
Colleges in sample	359	223
Number of observations	148,976	106,194
<i>Panel B: Tier 1 institutions without name change as comparison group</i>		
	(1)	(2)
	All name changes	College to university
Effect on average CEE score (in SD units)	0.029*** (0.004)	0.037*** (0.005)
Colleges that changed names	244	109
Colleges in sample	636	503
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  $\beta_1$  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 (mis)information in driving them. In this Appendix, 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 belief about various traits of the college at the time of choosing and the reality they encounter when they arrive.

### F.1 Data

We analyze of text from online discussions on the website [www.zhihu.com](http://www.zhihu.com). Zhihu.com is the largest Q&A platform in China, similar to the popular English-language Q&A site [quora.com](http://quora.com), and one of the most popular Chinese social media platforms among young people. 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.<sup>56</sup> 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) three-year colleges upgrading two four-year colleges; 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 20 million times, received roughly 40,000 likes, and had more than 22,000 posted comments.

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<sup>56</sup>These keywords were: *daxue gengming*; *daxue gaiming*; *xueyuan gengming*; *xueyuan gaiming*; *gaoxiao gengming*; and *gaoxiao gaiming*.

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 colleges discussed were either public colleges whose name change did not include the change from college to university (14.2%) or about private colleges' name changes (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) resource changes at name-changing universities; iii) the impact of name changes on CEE scores; iv) the impact of name changes on the employment prospects of graduates; and v) the putative "success" of the college's name change on 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 and classified keywords within each category by hand coding a set of 500 randomly selected replies. We list the specific keywords in each category in Table A.9. We associate each reply with the college being discussed and 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, whether the name change includes the change from college to university ( $Univ_i$ ), 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, affiliation, and the size of the city in which a college is located.<sup>57</sup>

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<sup>57</sup>The 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;

Table A.9: Word 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.

Our estimating equation is:

$$Y_i = \tau_0 + \tau_1 Univ_i + \tau_2 PrivSever_i + \tau_3 X_i + \varepsilon_i \quad (5)$$

By estimating the parameters  $\tau_1$  and  $\tau_2$  in Equation 5, we test two specific hypotheses. Estimating  $\tau_1$  allows us to gauge whether college names which include a change from college to university attract more attention, approval, or positive sentiment. Similarly, estimating  $\tau_2$  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 the success of the name change in raising score, 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

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.

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 classified as [0 = *No*, 1 = *Yes*] 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.<sup>58</sup>

### **F.3 Results**

We first report descriptive analyses of these data. To begin with, students appear to be aware of the phenomenon we observe in Section 3, that college name changes attract applicants with higher CEE scores, particularly among out-of-province applicants. Among the 3005 discussions used in our analysis, 151 (5.0%) of them explicitly talk about how new college names affect CEE scores of enrolled students. Among these discussions, 140 of them include assertions that new college names lead to higher CEE scores among enrolled students immediately after the name change, especially for out-of-province applicants.

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 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 5 for this and other anecdotes from the text data that illuminate this and a set of 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

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<sup>58</sup>Available at [https://ai.baidu.com/tech/nlp/sentiment\\_classify](https://ai.baidu.com/tech/nlp/sentiment_classify).



“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 Panel A of Table 4): that there exists a larger information gap between beliefs and the reality of the quality of the college among students from outside of the province in which the college is located than among those from the same province.

The gap between students’ beliefs and reality extends to the geographic location of the college. Fifteen out of the 336 information gap discussions report the experience of students who incorrectly inferred the location of their college 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 their “parent” universities 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 mother universities. This suggest that mother university names may be a symbol of high-quality college education, despite the fact that the management of independent colleges has nothing to do with parent institution.

The text in our data are far less likely to contain discussion of whether there are changes to 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 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 A.10. In this table, each column corresponds to a separate estimation of equation 5, 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. 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 A.10: Text analysis results

	<i>Attention received</i>		<i>Content of discussion</i>	
	(1)	(2)	(3)	(4)
	Log number of likes	Log number of comments	Name change perceived as successful	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 5, 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 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,” comprising largely 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:

$$Score_{iltc} = \kappa_0 + \kappa_1 NewName_i + \kappa_2 Male_i + \kappa_3 \vartheta_{lt} + \kappa_4 \theta_c + \varepsilon_{iltc} \quad (6)$$

This regresses the score of individual  $i$  in locality  $l$  at year  $t$  and college  $c$  on a constant, whether they graduated after a name change occurred, their gender, a locality-year fixed effect  $\vartheta_{lt}$ , and a college fixed effect  $\theta_c$ . We standardize the test scores to the city-by-year level. The main coefficient of interest is  $\kappa_1$ , which estimates whether applicants from graduating from a given college post-name change perform any better than applicants graduating from that same college before the name change.

Table A.11: Civil servant exam scores and college name changes

	(1) Overall test score	(2) Administrative skill score	(3) 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 6 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. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

This estimate is observational, not a causal impact of the name change on aptitude. 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 A.11. 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 4.5. 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 organizations. 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.