Improving college choice for the poorest students in centralized admissions: Experimental evidence on the importance of precise predictions*

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Abstract

This paper studies how admissions outcomes in centralized systems depend on college choice behaviors. Centralized admissions simplify the application process and centrally provide information but would reward informed strategic play in college choice. Centralized admissions can be difficult to navigate because they require students to understand how application portfolios and placement priorities map to admissions probabilities. Using administrative data from one of the poorest Chinese provinces, I show that low-income students make undermatched college choices that are correlated with inaccurate predictions of admissions probabilities. I then implemented a large-scale randomized experiment (N=32,834) to provide treated students with a guidebook or a guidebook and workshop combination. Results suggest that informing students on how to strategically choose which colleges to apply to, particularly based on precise predictions about admissions probabilities, can effectively improve college choice decisions and college-going outcomes.

Keywords: College choice, behavioral intervention, centralized college admissions

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1. Introduction

Inequality in college access and match persists: Low-income students, facing various barriers at every stage of their educational pipeline, are much less likely to attend college and particularly selective institutions (Holsinger and Jacob, 2009; Bailey and Dynarski, 2011; Li et al., 2015). In recent years, the complex transition from high school to college has been increasingly recognized as an important barrier for students, particularly those from disadvantaged backgrounds (Lavecchia, Liu and Oreopoulos, 2016; Page and Scott-Clayton, 2016). In particular, even when low-income students reach the college choice stage, they are more likely than their high-income peers to apply to and enroll at colleges that are not matched to their academic achievements. That is, they undermatch (Bowen, Chingos and McPherson, 2009; Hoxby and Avery, 2013; Smith, Pender and Howell, 2013; Dillon and Smith, 2017*b*). Undermatched college choice significantly lowers their chances of college and career success (Howell and Pender, 2016; Dillon and Smith, 2017*a*; Kang and Torres, 2018; Ovink et al., 2018). The undermatch problem is prevalent not only among American low-income students, but also in many other countries such as Chile (Hastings, Neilson and Zimmerman, 2018), China (Loyalka, Wu and Ye, 2017), and Russia (Prakhov and Sergienko, 2017).

During the past decade, behavioral interventions, including both light-touch information provision and intensive personalized advising, have been widely proposed and implemented as promising policy tools to help students navigate the complex transition from high school to college.[1] This rapidly growing literature of college choice interventions mostly focuses on the decentralized admissions systems in the U.S. and Canada, little is known about what works in other contexts.[2] In particular, many countries use centralized college admissions with mandatory entrance exams and a simplified application process, in which information is no longer the primary barrier. Instead, centralized admissions may reward informed, strategic applications that students need to understand how application portfolios and placement priorities map to admissions probabilities (Kapor, Neilson

[1]Recent summaries include Thaler and Sunstein (2008), White House (2014), Castleman, Schwartz and Baum (2015), Lavecchia, Liu and Oreopoulos (2016), Page and Scott-Clayton (2016), Castleman (2017), French and Oreopoulos (2017), and Damgaard and Nielsen (2018).

[2]A small body of literature has examined light-touch information about the benefits of college and major, financial aid, role model, and the importance of test scores. (Dinkelman and Martínez A, 2014; Hastings, Neilson and Zimmerman, 2018; Herber, 2018; Peter, Spiess and Zambre, 2018; Bonilla-Mejía, Bottan and Ham, 2019).

and Zimmerman, 2020).[3] Whether and how strategic college choices affects admissions outcomes in centralized systems remains as an open question.

In this paper, I provide one of the first evidence on college choice behaviors and admissions outcomes of low-income students under centralized college admissions. Using administrative data from one of the poorest Chinese provinces, I show that low-income students make undermatched college choices that are correlated with inaccurate predictions of admissions probabilities. Focusing on the critical role of strategically choosing which colleges to apply to in a centralized system, I conducted a large-scale randomized controlled trial (RCT) with high school graduates of the 2016 graduation cohort. Collaborating with the local government and high schools in Ningxia province, I designed and implemented the *Bright Future of China Project* to understand and address the academic undermatch problem by improving students' college choice behaviors.[4] This large-scale experimental design helps to make progress on two important research questions: (1) What are the sources of undermatch regarding (un)strategic application behaviors in centralized college admissions? (2) Do behavioral interventions focusing on precise predictions of admissions probabilities affect students' college choice behaviors and admissions outcomes?

The empirical analysis begins by documenting the full extent of student-college academic undermatch in a centralized college admissions system. Using administrative data on students' college admissions, the results indicate that - as is true in decentralized admissions - academic undermatch is also prevalent in centralized admissions. Using a very conservative bandwidth of 0.25 standard deviations, students from urban families have an average undermatch rate of 23.1 percent.[5] Rural students - a common proxy for poor students in developing countries - are 9.8 percentage points more likely to undermatch. This poverty gap in undermatch persists when comparing two

[3] In countries like Brazil, Chile, China, Germany, Greece, India, South Korea, Turkey, and the United Kingdom, college admissions operate through national exams and a centralized application and admission system (Neilson, 2019). In line with the growing adoption of centralized admissions in K-12 school choice, many U.S. colleges are starting to use the Common Application, a platform through which students may submit the same application to as many colleges and universities as they like.

[4] Our research team named this project before knowing that the College Board has a similar program with a similar name ("Big Future"). Apparently, we all hope to help students gain bright/big futures.

[5] Undermatch is defined to equal one if a student enrolls at a college with a median College Entrance Exam (hereafter CEE) score 0.25 standard deviations lower than her own CEE score, or if she does not enroll at college. The undermatch rate will increase when using a smaller bandwidth.

students in the same classroom with the same CEE score and demographic characteristics.

Next, I use unique data of students' college applications to investigate the correlation between a set of measures of college choice behaviors and admissions outcomes. This unique data enables me to identify students' strategies and preferences in college applications. Results show that many students, particularly low-income students, do not use appropriate college application strategies that would improve their college access and match. The descriptive evidence indicates that the most important factor in college choice behaviors driving undermatch is that students do not use targeting strategies based on precise predictions of college admissions probabilities. The targeting strategies enable students to apply to a mixed set of reach, peer/match, and safety colleges, which minimize the risks of being rejected by all the applied colleges and maximize the chances of being admitted to a higher-ranked college. Hoxby and Turner (2013) describe this as expert advice that high-income students often use in their college choices.

I then ask *whether informing students on how to strategically choose which colleges to apply to improve college applications and admissions in a centralized system.*[6] Access to information - college attributes, admissions policies, and admission data in prior years - is not enough because students need to understand the admissions mechanisms and conduct intensive data analysis to correctly and precisely estimate the admissions probabilities associated with different application portfolios. Students who often lack such ability may have behavioral responses to the complicated decision-making. For example, they may just use very "simple and sometimes naïve" choice rules, such as choosing a college or major based on its name. Even when some students engage in the strategic play, they often make incorrect predictions different from rational expectations.[7]

To help students make informed college choices, I designed a college application guide that focuses on the precise predictions of college admissions. This intervention design differs from

[6] A few interventions are considered to be very ineffective or not in need in centralized systems, such as reminders (students receive a series of text messages from the Department of Education), application fee waiver (students already pay for the very low college entrance exam testing and application fee), information/nudge/assistance of the application procedure (simple and straightforward), information about college return (almost all students are motivated to attend college), and information about college cost (centrally provided by the Department of Education).

[7] Kapor, Neilson and Zimmerman (2020) report quite similar problems in the centralized school choice setting in New Haven, CT. Mulhern (2019) shows that, in the U.S. decentralized admissions, students' college choices are substantially affected by personalized admissions information.

existing literature by “teaching students to make rational predictions” instead of simple information provision or advising/counseling related to the application procedure. I prepared a comprehensive college choice and application guide - a college application guidebook - to help students gather information, as well as learn the rules and principles for college-going decisions. The focus of the guide is making accurate predictions of admissions probabilities. In this way a student can make an informed, strategic college choice by themselves. I also provided school workshops to promote students learning of the guidebook. Using stratified cluster randomized experiments, 32,834 high school graduates in Ningxia were randomly assigned to one control group or two treatment groups that received (1) a guidebook, and (2) a guidebook-school workshop combination during the five-day college application period in late June (see summary in Table B.1).

The experimental evidence shows that the precise prediction-based interventions, during a short time period with low costs, substantially improve college admissions outcomes. Students in the two intervention arms on average are admitted to colleges with a 0.094 (0.076) s.d. ($p<0.05$) higher quality. The improved college access and match is primarily through shaping students’ college application behaviors. Both the guidebook only and the guidebook-workshop combination interventions have increased students’ use of targeting strategies that are based on precise predictions of college admissions probabilities by more than 100 percent. Students are more likely to apply to a mix of reach, match, and safety colleges and rank these colleges in a descending order of predicted admissions cutoffs. Importantly, the college applications based on precise predictions do not improve college admissions outcomes at the cost of substantially changing students’ other preferences such as tuition, admissions quota, special programs, and majors. Additionally, as expected, the interventions have nudged students to consider out-of-province (and higher quality) college options. These results are consistent with the intervention designs.

This paper makes several contributions to the literature. First, it provides new evidence about student-college academic undermatch and its potential sources regarding application behaviors in centralized admissions. The results suggest that simplifying the college application process and providing a centralized information platform may not fully address the undermatch problem. Given the importance of application strategy and sophistication in centralized admissions systems, the use of strategies - especially those for making precise admission probability predictions - is the key driver of matched college choices and admissions. I also find that distance is an important factor that shapes students' college choices, and that focusing on in-province colleges would limit students' high-quality college opportunities because low-income regions are often "college deserts" (Hoxby, 2000; Long, 2004; Hillman, 2016; Ovink et al., 2018). I do not find evidence that preferences for tuition, admissions quotas, and majors largely affect students' college access and match in centralized admissions.

More importantly, this paper contributes to a growing literature on the effectiveness of behavioral interventions for the complex transition from high school to college (see the recent summaries in White House, 2014; Page and Scott-Clayton, 2016; J-PAL, 2018). The existing literature primarily focuses on students in the U.S. and Canada. Very limited evidence is available about what works in improving college decisions in centralized systems or in developing countries.[8] Centralized admission is widespread across countries in both K-12 and higher education. While it streamlines and simplifies the application process, it may require strategies and sophistication in decision-making, so that one may expect to see differences in the effectiveness of existing behavioral interventions (Pathak and Sönmez, 2013; Chen and Kesten, 2017). This paper provides novel evidence on the impacts of application assistance interventions in the use of knowledge, as opposed to information provision and application simplification, from the largest centralized college admissions market in the world.

The intervention designs build on many prominent approaches, including information provision (Hoxby and Turner, 2013; Goodman, 2016; Peter and Zambre, 2017; Herber, 2018; Evans and Boatman, 2019), text message reminders (Castleman and Page, 2015), advising/counseling (Bettinger et al., 2012; Castleman, Owen and Page, 2015; Carruthers and Fox, 2016; Carrell and

[8]Experimental evidence on centralized admissions is limited, with few exceptions such as Hastings, Neilson and Zimmerman (2018) and Peter, Spiess and Zambre (2018) in higher education, and Corcoran et al. (2018) and Kapor, Neilson and Zimmerman (2020) in the U.S. school choice. Many U.S. college admissions officers and high school counselors advocate for a centralized system to simplify college choice, see a 2014 Washington Post article "What if Google ran the college application process?"

Sacerdote, 2017; Oreopoulos, Brown and Lavecchia, 2017; Page et al., 2017; Castleman and Goodman, 2018; Gurantz et al., 2019), and school workshops or services (Oreopoulos and Ford, 2016; Bowman et al., 2018; Bettinger and Evans, 2019). This paper demonstrates an effective researcher-initiated, problem-solving intervention approach that focuses on informing students on making precise predictions of college admissions probabilities. The finding of effectiveness of strategized college application interventions such as guidebooks, workshops, and personalized advising, is also consistent with recent literature in decentralized or non-selective admissions. For example, Oreopoulos and Ford (2016) show that school workshops that guide students' college applications increase community college applications and enrollment. Carrell and Sacerdote (2017) suggest that college mentoring substitutes for the potentially expensive and often missing ingredient of skilled parental or teacher time and encouragement. However, the treatment effect does not derive from simple behavioral mistakes or a lack of easily obtained information; this paper shows that strategic play based on a sound understanding of the admissions mechanisms and data analysis would help college-bound students make better decisions, especially when they face too many options. Mulhern (2019) shows that the personalized admissions information shifts applications and attendance to colleges for which students can observe information on schoolmates' admissions experiences. This paper suggests that helping students to better analyze such information or to make individualized, precise predictions is an important space for relatively low cost policy interventions that could improve their college-going outcomes.

2. Background

2.1. College Choice and Centralized Admissions

College choice is complicated. Conventional college choice models (for instance, Manski and Wise, 1983; Long, 2004; Perna, 2006; Perna, 2006; Jacob, McCall and Stange, 2018) assume that rational and forward-looking college applicants choose from a feasible set of colleges the one that maximizes their expected utility.[9] The benefits of college include both "monetary" human capital

[9]College choice, in general, includes several stages. For example, Hossler and Gallagher (1987) propose a three-phase model (predisposition, search, and choice); DesJardins, Ahlburg and McCall (2006) jointly model the application, admission, financial aid determination, and enrollment decision process. This paper focuses on a student's decisions about which colleges to apply to.

returns and "non-monetary" preferences (college and major attributes such as selectivity, college type, cost, distance, and consumption amenities, e.g., Jacob, McCall and Stange, 2018; Ovink et al., 2018).[10] However, college applicants are often highly sophisticated information processors. The differences in college choice that are not explained by the standard college choice model might result from two behavioral factors: (a) unequal access to information (see summaries in Page and Scott-Clayton, 2016 and Castleman, 2017) and (b) heterogeneous beliefs and strategic behaviors (Bénabou and Tirole, 2016; Kapor, Neilson and Zimmerman, 2020).

To examine the importance of precision predictions of admissions probabilities in centralized admissions systems, I expand the multi-stage college choice model (Hossler and Gallagher, 1987; DesJardins, Ahlburg and McCall, 2006) by detailing the steps to make informed decisions about which colleges to apply to. Students in both decentralized and centralized systems need to go through the same decision-making process, which consists of four steps:

(1) Search for college and major information (in Chinese college admissions, a student may have more than 20,000 college-major options);
(2) Collect and understand college admissions policies;
(3) Identify reach, match/peer, and safety colleges based on predictions of admission probabilities;
(4) Apply appropriately to a list of reach, match, and safety colleges (and majors).

The first two steps, regarding information and preferences, could be addressed by light-touch informational interventions. Even with the same access to information, steps (3) and (4) require sophisticated decision-making.[11] For example, Hoxby and Avery (2013) note that the expert advice concerning college application is to apply to several "peer" colleges, a few "reach" colleges, and a couple of "safety" colleges. This advice itself is simple information. However, knowing this advice is not enough because identifying college types requires skills to gather and analyze the SAT/ACT

[10] The "College Search" section of the College Board has ten filters: test scores & selectivity, type of school (2-year or 4-year, public or private, size, sing-sex or coed, religious affiliation), location, campus & housing, majors & learning environment, sports & activities, academic credit, paying, additional support programs, and diversity.

[11] Avery and Hoxby (2004) find that students have different behavioral responses to what might objectively be viewed as similar dollar amount changes in the costs and benefits of college attendance. It can be viewed as a framing effect or nudge (Thaler and Sunstein, 2008; Benkert and Netzer, 2018), but it can also result from lack of knowledge to fully understand the real meaning of various forms of financial aid when they are labeled "grant" or "scholarship," and whether they are front-loaded.

and GPA information of each college. Correctly predicting admissions chances is the key to forming a reasonable application portfolio with a set of reach, match, and safety colleges.

Every year, millions of high school graduates go through these four steps to apply for college admissions worldwide. In some countries, like the United States and Japan, college admissions are decentralized. Students must apply separately to each college and colleges make their decisions independently. Admissions results are often based on a number of performance measures including SAT or ACT scores (mandatory test improves college enrollment, see Bulman, 2015; Hyman, 2017), high school grades, recommendations, and personal statement. In many other countries like Brazil, Chile, China, Germany, Greece, India, South Korea, Turkey, and the United Kingdom, college admissions are operated through national exams and a centralized application and admission system. Admissions results are solely determined by the exam score and students' ordered college choices.

Compared with decentralized admissions, centralized admissions are simplified and less costly.[12] In addition to taking the required, often nationally centralized college entrance exam, students only need to submit their rank-order lists of colleges. They can apply to many colleges simultaneously and submit their applications online at a minimal or zero cost. Centralized systems can also provide all the information relevant to students' college applications, which addresses the common informational barriers in decentralized systems.

Although the application process is simplified and information is accessible, students in centralized admission still face behavioral barriers that emphasize on the role of sophistication. When they apply to a rank-order list of colleges to maximize their expected utility, there are several constraints due to common institutional features. First, admissions are implemented with a list of restricted length in many real-world examples, in which truthful revelation of preferences is no longer the optimal strategy (Arslan, 2018; Chen and Kesten, 2017). Second, many centralized systems only match students to at most one option, which imposes a high risk of all applications

[12]The expensive testing and applications in decentralized admissions may prevent students from applying to many colleges. Chade, Lewis and Smith (2014) note that a median American high school student applies to three colleges. Pallais (2015) finds that students strongly respond to an extra free college application (6$) in the SAT. Regarding the increased number of free ACT score reports available to low-income students, Hurwitz et al. (2017) also find positive effects on college attendance and degree completion of free SAT reports.

being rejected. Students have to evaluate the *ex ante* admissions probability of each college based on the admissions outcomes (for instance, cutoff or median admission scores) in the prior years. Third, the centralized admissions may occur during a short time period. In order to make a thorough search and carefully assess college fit, students have to very quickly and efficiently search for and analyze a large volume of college information from reliable sources.

Given these barriers, the complication of college choice is mainly driven by the significant uncertainty in college admissions (Chade, Lewis and Smith, 2014). In order to construct a thoughtful application list with a set of reach, match, and safety colleges, students have to make accurate predictions of admission probabilities using available information and make educated inferences. But students can make costly application mistakes if they incorrectly predict admissions chances due to lack of sophistication, misunderstanding the admissions policies, or limited ability to conduct "big data" analytics (Pathak and Sönmez, 2008; Kapor, Neilson and Zimmerman, 2020).

2.2. Context: Centralized College Application and Admissions in China

China has the world's largest centralized college admissions system. China's college application and admission procedures are centralized at the province (state) level. Students only compete for college-major spots with peer applicants within the same province and STEM/non-STEM track. The process begins with the administration of the annual national College Entrance Examination (hereafter and before CEE) in early June, similar to the SAT/ACT in the United States. The CEE scores are the sole criteria used to rank the priorities of students in college admissions. High school seniors take four subjects: Mathematics, Chinese, English, and track composite. Students choose either the STEM track with exams in physics, chemistry, and biology; or the non-STEM track with exams in history, social studies, and geography.

Next, all the Chinese colleges allocate their college-major admissions quotas to each province and publish their quota and tuition information. All the information is provided to students by the provincial Department of Education in mid-June. After knowing their CEE scores in late June, students submit their college application lists to the provincial Department of Education. Students who choose not to apply to any college do not submit applications. The list includes 4-10 colleges for each institutional tier, varying across provinces, in which they rank colleges and majors within each college (4-6 majors for each college). The submission process is very simple in that students only need to type in the college and major IDs in the online system. In Subsection C.1, I show and explain in detail a typical college application form in China.

College application and admission proceeds by institutional tiers. Tier 1 includes the nation's elite colleges. Tier 2 and Tier 3 consist of non-elite public and private four-year colleges, respectively. Tier 4 includes three-year vocational colleges, which resemble community colleges in the U.S. Tier 1 and Tier 2 colleges are selective and admit the top 30%-40% of applicants. Tier 3 and Tier 4 colleges are mostly open admissions and admit about 40% of the applicants who are relatively lower-achieving. Each year, about 20 percent of CEE takers are not admitted by a college: About 10 percent do not apply to any colleges, and the other 10 percent apply but are rejected.

Student application eligibility is limited to colleges in certain tiers based on their CEE score and the tier-specific admission cutoff scores, which are determined by the total number of spots and the distribution of the CEE score within the province. That is, students with CEE scores above the Tier 1 cutoff are allowed to apply to colleges in all tiers. Students with CEE scores between the Tier 1 and Tier 2 cutoffs are only allowed to apply to Tiers 2-4 colleges, but not Tier 1 colleges. Within each tier, there might be additional special admissions programs that allow the eligible students to submit a separate application list. Special admissions include race- and income-based affirmative action programs, and early admissions for selected majors. A student can apply to more than 50 colleges (she does not have to) or just 1 college.[13]

Based on their CEE scores, each student is then matched with only one college-major in their college application list through a predetermined matching mechanism. Like many Chinese provinces, Ningxia currently uses a parallel mechanism like the Deferred Acceptance mechanism (see discussions in Chen and Kesten, 2017). Each student receives a single take-it-or-leave-it

[13]It is not an optimal strategy to apply to too many or too few colleges. For the former, special admission programs, which are undermatched options for some students, complete admissions before the normal programs. Applying for these special programs without careful consideration may result in undermatched college admissions. For the latter, applying to too few colleges limits one's chances of trying reach or match colleges, and increases the risk of all applications being rejected.

admission offer for the college-major to which they are matched. Some students may not be accepted by any college. If a student declines the offer, or does not receive an offer, she must wait until the following year to retake the CEE and participate in the matching process again. The alternative is to enter the job market or to enroll at a university outside China.[14]

2.3. Research Site and Data Sources

This paper studies college application behaviors and admissions outcomes using data from Ningxia province, one of the poorest provinces with a typical centralized college admissions system. Ningxia, officially the Ningxia Hui Autonomous Region, has the third smallest total GDP in China where Muslims are more than 38% of its population. Most of the region is desert, making Ningxia one of the poorest provinces in northwestern China.[15] I focus on both rural and urban students because, in fact, most of them are from low-income families. Each year, nearly all high school graduates (about 60,000) take the College Entrance Exam.[16] About 90% of the exam takers apply to college and 85% are admitted to college, but fewer than 10% are admitted to elite colleges.

I use unique, large-scale student level administrative data for the universe of 2016 high school graduation cohort in Ningxia. The data are provided by the Ningxia Department of Education and the Ningxia Education Examination Board, the provincial centralized administration office of the College Entrance Exam and college admissions. The confidential student-level data are from four separate sources: (1) College Entrance Exam Registration Data that include student demographic information, high school attendance records, and graduation test scores (low-stakes); (2) College Entrance Exam Score Data that include all the CEE score information (high-stakes) ; (3) College Applications Data that include all the rank-order application lists that students submit to the Ningxia Education Examination Board; and (4) College Admissions Data that include the admissions results of all students who have submitted their applications. I linked all of these student-level

[14] Very few students make the oversea college plan after taking the CEE. Those who aim to study abroad usually do not take the CEE and most of them have already made the enrollment decisions before the CEE in June.

[15] Appendix Figure A.1 shows the geographic location of Ningxia. In 2017, the annual per capita disposable (after tax) income of urban residents is about $4,200 (national average: $5,600), and that of rural residents is $1,650 (national average: $2,060). About 800,000 of Ningxia's 6 million population are under the extreme poverty line due to earning less than $1 a day.

[16] This is a highly selected population of "lucky" students who have overcome all the barriers from birth to grade 12. Nationally, only about 40% of a birth cohort (18 million) could reach the stage of college application.

administrative data using a unique student identifier. The analytical data are de-identified.

I merged the college-major level information (address, tuition, quota, prior-year admissions scores) with the student-level data to study their college choice behaviors, measured as strategies and preferences, and college match outcomes, which will be discussed in detail in Subsection 3.2 and Subsection C.1. This college-major level information is also provided to students during the college application period by the Ningxia Department of Education in print books.[17] In addition, confidential school finance data from the China Ministry of Education were used for the school-level randomization in 2016.

3. The Policy Challenge

3.1. College Undermatch in Centralized Admissions

During the past decade, student-college academic undermatch has drawn concern from education researchers and policymakers. It is widely believed that approximately 20 to 70 percent of American high school graduates undermatch (estimates vary across data, sample, and methods). Researchers have used various definitions of undermatch mainly due to data availability or specific research questions (see summary discussions in Rodriguez, 2015; House, 2017), including comparing student academic credentials with college selectivity (Roderick et al., 2008; Bowen, Chingos and McPherson, 2009; Smith, Pender and Howell, 2013), student ability percentile and enrollment weighted college quality percentile (Dillon and Smith, 2017*b*), and comparing a student's SAT/ACT score with a college's incoming freshman cohort median score (Hoxby and Avery, 2013).

To best describe the extent of undermatch in the Chinese centralized college admissions system, I take advantage of the centralized system itself. Moreover, the data enable me to study an entire college matching market to construct several college access and match measures. Speaking to the literature, I first constructed an "undermatch" indicator, which equals to 1 if a student is admitted to a college with a peer median CEE score 0.25 standard deviations lower than her own CEE score, or when the student is not admitted to any colleges. Table 1 shows that this measure presents a slightly smaller overall undermatch rate (28.6%) to that (33.5%) from the five-percentile

[17] The necessary information is available to all students. But the delivery using print books imposes high search and analytical costs for students to make optimal choices and decisions.

threshold as proposed in Hoxby and Avery (2013).[18]

I measure college undermatch on both extensive and intensive margins. The extensive margin measure is a dichotomous indicator of college admissions (=1). For the intensive margins, I consider several measures in addition to the undermatch indicator as described above, which jointly denote the college match results. I use college median, mean, and minimum scores of the incoming freshmen in the same year to measure contemporaneous college match.[19] Holding one's CEE score constant, a negative difference in college peer quality - resulting from the same year's college admissions - means that a student has "wasted" her CEE score to be undermatched with that college. To minimize the potential bias of using the college admissions results in a single year and in a single province to denote college quality, and to compare results across years, I use two national college quality measures: standardized score and ranking percentile.[20] Using these five intensive margin measures of college match, I construct a single index using principal component factor analysis as the primary college match outcome measure.

Quantifying college undermatch. In this section, I use the sample of untreated students from the 2016 graduation cohort in Ningxia. I include both the control group of the randomization sample and those not in the randomization sample that will be introduced in Section 4.[21] Table 1 documents the full extent of academic undermatch in a typical centralized admissions system in China. The rows represent students' CEE score quartiles, indicating to which quality level students have access. The columns show the college quality level to which a student is eventually admitted. The student-college match in centralized admissions is very similar to that in decentralized admissions, notably in the U.S. literature (for instance, Smith, Pender and Howell, 2013, Dillon and

[18]The choice of 0.25 s.d. as a conservative threshold is based on the practical experience of college choice advising in China. Table B.2 shows that the results remain qualitatively unchanged using other thresholds. Throughout the paper, all the results using these various undermatch indicators remain consistent.

[19]The results remain unchanged if I use leave-one-own-out scores. For students who are not admitted by any college, I assign the tier-specific lowest college median/mean score minus 0.2 s.d. as their "college median/mean score." In Figure A.2, I show that the results are very consistent using different measures for this group of students. The estimates correspond to the regression results of identifying the rural-urban gap in Table B.3.

[20]Using college admissions data from 1996-2017 and administrative data on institutional resources for every college in China, I build a national college ranking of all Chinese colleges, which is now published at siminedu.com to assist all Chines high school graduates in their college choices.

[21]The college access and match measures are constructed using the whole cohort data. Results are very similar using data from previous cohorts (Loyalka, Wu and Ye, 2017).

Smith, 2017*b*). Students show an assortative matching pattern such that 65.9 percent of students concentrate along the diagonal. However, about 25 percent of students are admitted to a college that is one quality level below the level to which they have access. The change in overmatch is not accordingly symmetric as noted by Dillon and Smith (2017*b*): 9.1 percent of students end up with overmatched colleges based on the quartile matrix. Using the undermatch indicator as discussed above, there are 28.63 percent of students who are admitted to a college with a median CEE score 0.25 standard deviation lower than their own CEE scores.[22] About 12% of the students enrolled at overmatched colleges.[23]

The undermatch statistics vary substantially by student achievement levels. The third CEE quartile students, facing the choice between four-year colleges and three-year vocational colleges, have the highest undermatch rate. The pattern is different from that in decentralized systems. First, students in the highest CEE score quartile have a lower undermatch rate than lower-achieving students. More than 90 percent of students in the highest CEE score quartile are admitted to the highest quality quartile colleges. This is partly due to the tier-specific admissions policy that guides higher-achieving students to apply to higher-quality colleges. Second, not being admitted to and then not enrolling at any college is an important source of undermatch not only for the lowest CEE score quartile but also for students in the second and third quartiles. This result suggests that college admissions are pretty risky in centralized admissions.

Poverty gap in college undermatch. The undermatch literature in decentralized admissions has well documented that disadvantaged students are more likely to undermatch. I focus on the poverty gap, using rural *hukou* as a proxy for poverty. *Hukou* is household registration, and is the primary source of income inequality in China.[24] In developing countries, there are often large gaps

[22]The national average undermatch rate for those admitted by four-year colleges decreased from 30% in 2005 to 15% in 2011, mainly due to the change from the Boston mechanism to the Deferred Acceptance mechanism.

[23]The few students who were in the low CEE quartiles but enrolled at elite colleges were mainly through special programs.

[24]The urban-rural income gap has been institutionalized by the *hukou* system since 1955 in China, under which all households had to be registered in the locale where they resided and also were categorized as either "rural" or "urban" households. Assigned at birth on the basis of the mother's registration status, *hukou* limits rural residents from migrating into the urban areas and entitles few of the rights and benefits that the government confers on urban residents, such as permanent employment, medical insurance, housing, pensions, and educational opportunities for children. See more discussions in Wu and Treiman (2007).

between rural and urban families in socioeconomic status, parental education and income, and information. Figure 1 provides graphic evidence of the sizable rural-urban gap in student-college undermatch. Compared with students in urban families, rural students are much more likely to undermatch. This gap exists among both high-achieving and low-achieving students, and it is larger among higher achieving students.

I use a linear model to formally estimate the poverty gap in college access and match:

$$Y_i = \beta_0 + \beta_1 * Rural_i + \gamma * X_i + \varepsilon_i \tag{1}$$

where β_1 measures the rural-urban gap in the college match outcomes Y_i, with standard errors clustered at high schools. I add additional covariates X_i (CEE score, demographics, and class fixed effects) stepwise to examine how well these factors explain the observed rural-urban gap. Since centralized admissions are solely determined by exam scores and the college choices of students, holding exam scores constant, I can directly identify the relative undermatch between two groups by comparing the differences in college admissions outcomes.

Appendix Table B.3 presents results on the rural-urban gap in college access and match.[25] Within each panel that uses different model specifications, each cell shows the estimates from a separate regression. The results show that, holing demographics and CEE score equal, disadvantaged students in a Chinese centralized system statistically significantly and substantially undermatch more than advantaged students on both extensive and intensive margins. This large poverty gap is solely driven by the rural-urban differences in college choice behaviors.[26]

While urban students have an average admission rate of 87.9 percent, rural students are 6.7 percentage points ($p<0.01$) less likely to be admitted by a college (Column 1 Panel C). This is due to both a lower application rate and a lower admission rate conditional on application. Table B.5 shows that rural students are 2.9 percentage points less likely to apply to college. Rural students on average are admitted to colleges with a 0.18 s.d. lower quality than those of urban students (Column

[25] Table B.4 decomposes the five outcomes that I use to construct the college match index. Results are very similar using the in-province measures or the national measures.

[26] In the regression results of Table B.3, female, minority, older, and lower-achieving students are more likely to undermatch. Repeaters are much less likely to undermatch, suggesting the potential benefits of repeating grade 12 in information and experience of college applications.

3 Panel B). Even conditional on being admitted to a college, rural students are admitted to colleges with a 0.08 s.d. lower quality (Column 3 Panel C). [27] Controlling for class fixed effects in Panel D (an average class has about 59% rural students) reduces about one third of the rural-urban gap in college undermatch. Students in the same class may share information and assistance from teachers simultaneously. However, the large within-class poverty gap suggests that improving college access and match in these centralized systems remains an open and challenging question.

3.2. The Importance of Precise Predictions and the Potential for Behavioral Interventions

I explore student behaviors in college applications in order to set the stage for designing policy interventions to improve college access and match at scale. I use the full college applications data of those untreated students in 2016 to test what matters in college choices. Based on the theoretical framework of the four steps in college applications, I use the observed behaviors in college applications to construct a list of key strategies and preferences that students have. Appendix Subsection C.1 provides a detailed description of these measures, which in particular explains the behavioral rationales of these choice behaviors.

First, I focus on three sets of measures of application strategies: (1) general advice, (2) targeting, and (3) special program application. *Targeting strategies* are the core decisions to precisely predict admissions probabilities in order to generate a reasonable application portfolio of a combination of reach, match, and safety colleges. The use of targeting strategies first requires sound understanding of the underlying mechanisms of college admissions: ranking percentile (not the raw score) matters. Many students (a 65% estimate in this paper) naively compare their CEE score in this year with college admissions raw scores in the previous years, which results in mistakes of identifying college types.[28] Students also need to understand that the rank-order of colleges

[27] Table B.5 shows that rural students are less likely to apply to and enroll at college, they are more likely to retake CEE in the next year, and they are less likely to enroll at matched or overmatched colleges.

[28] Many students do not understand the underlying mechanism of college admissions: Only rank matters, not raw scores. They naively compare their CEE score in this year with raw college admissions scores, which results in large errors when identifying college types. Figure A.3 shows the distribution of student applications. The X-axis shows the distance of college median score and a student's own score. I separately present the distributions for a student's first choice and fourth (last) choice in the match tier. It clearly shows that, though correctly centered, some students apply to match colleges (and in the order that the first choice should aim higher than the last one). However, a large proportion of students apply to colleges that they will be substantially undermatched to, or apply to colleges that they have a nearly

in their application list matters as well. This means that they should rank reach colleges above match and safety colleges. Identifying types of colleges based on predicted admissions probabilities substantially depend on one's ability and sophistication to perform large-scale data analytics.

Next, the other important aspect of college choice is preference. However, students' preferences and tastes are individual-specific and strictly unobservable. Particularly in constrained college applications, revealed preferences may not be exactly students' true preferences. I constructed three sets of proxy preferences using the applications data. The first set includes college tuition and quota. Low-income students may prefer low-tuition colleges, and risk-averse students may prefer colleges with larger admissions quotas (Hoxby and Avery, 2013; Loyalka, Wu and Ye, 2017). The second set includes geographic location (indicators for colleges out of province or in the economically developed regions). The last set includes a few major group indicators to capture students' major preferences.

Figure 2 presents a set of pairwise correlations comparing the primary college match outcome - college median CEE score - with the (partial) list of the itemized measures of college choice strategies and preferences as described above. Targeting strategies are the most important predictors correlated with improved college match. In Table 2, I extend Equation 1 by including the measures of the constructed strategies and preferences to examine how much they could explain the rural-urban gap in college match. Consistent with the differences in admissions outcomes, rural students are less likely to use appropriate strategies such as flexible major assignment and targeting applications, and are much less likely to choose out-of-province colleges. Comparing the changes in the coefficients on rural-urban gap, targeting strategies explain the largest variations in the outcomes among all the strategies and preferences, even controlling for CEE score, demographics, and high school fixed effects. Alternatively, an Oaxaca-Blinder decomposition tells a very consistent story. About 0.078 s.d. of the 0.132 s.d. (59%) estimated rural-urban gap (rural mean: 0.058; urban mean: 0.189) in the college match index, controlling for CEE score and demographics, is explained by rural-urban

zero chance of getting into. In 2018, I provided online advising to more than 30,000 high school graduates across China (not a randomized experimental sample). Score equating and targeting the match colleges is the single most important question that the students had.

differences in the college choice strategies and preferences that I constructed. The set of targeting strategies explain a 0.065 s.d., or 83% of the explained difference in the rural-urban gap.

Together, this section's descriptive analysis demonstrates the importance of precise predictions of college admissions probabilities in a typical Chinese centralized system. Students in low-income areas such as Ningxia show that they may have informational and behavioral barriers in college applications. They generally do not use appropriate strategies that would increase their college access and match. Poorer students show more severe problems and therefore are more likely to undermatch. Of all the strategies and preferences, the targeting strategies based on precise predictions seem to be the most important and promising element of a behavioral intervention for low-income students.

4. Experimental Design

4.1. Interventions: Informing Students on Precise Predictions of College Admissions

I used a large-scale randomized controlled trial to test whether informing students on precise predictions of college admissions improves college choice decisions and college-going outcomes. Considering what actions an expert counselor or a very sophisticated student would take for the decision-making, I prepared a comprehensive college choice guide with the focus on precise predictions of college admissions. I designed two school-based channels to deliverer the same application guide materials: (1) a booklet and (2) a school workshop.

The intervention design in the *Bright Future of China Project* builds on the Application Strategies approach of the Expanding College Opportunities project in Hoxby and Turner (2013).[29] It combines features of both informational interventions and individualized advising/nudging examined in a wide body of literature (see summaries in Page and Scott-Clayton, 2016; J-PAL, 2018). I focus exclusively on the instruction and learning of the sophisticated college choice strategies during a very short time period (one week) when students apply to college.

[29] I do not incorporate the other interventions in Hoxby and Turner (2013) and other related studies including cost information, application fee waiver, and parent intervention. In the Chinese centralized admissions, students are provided with tuition information for every college-major, and institutional financial aid is rare. College application fees are low (25$ with exam fees included). Nearly all high school seniors take the college entrance exam. In low-income areas, average schooling level of parents is lower than junior high school, which makes using any written materials mailed to parents ineffective.

I led an expert team to prepare the "How to Apply to College?" guidebook. The team included professors and graduate students in the field of both K-12 and higher education policy, school counselors, and college admissions officers in China. Using our expertise in advising college choice for more than a decade in China and conducting additional learning from many prominent sources,[30] our research team produced a very comprehensive guidebook. With regard to the key steps and strategies in college choices and applications, the guidebook is designed to consist of four main "course" modules: (1) searching for college information, (2) understanding admissions policies, (3) equating CEE scores and predicting college admissions probabilities, and (4) applying to an optimal portfolio of colleges. To supplement the main modules, I also make use of both large scale (and confidential) databases as well as reliable information about colleges and college applications.

In advising students about how to search for information, I provide a table that maps a list of recommended websites of college and major information (panel A of Figure C.2).[31] To assist students with major choice, I use the post-graduation employment data of the universe of Chinese college students from 2011 to 2014, a dataset with over 30 million observations, to show the employment rate trends (panel B of Figure C.2). Lastly and most importantly, I provide detailed explanations of the college admissions policies and then actionable strategies to generate an optimal portfolio of colleges based on precise predictions. Subsection C.2 provides detailed descriptions and sample pictures (Figure C.1) of the guidebook.

The guidebook was not designed to change students' college and major preferences as it was not tailored to individualized applications. The exception is that I strongly nudged students to apply to out-of-province colleges. The "home bias" in college choice often limits high-quality college opportunities (Hoxby, 2000; Long, 2004; Hillman, 2016; Ovink et al., 2018). Our previous work suggests that the preference for in-province colleges results in large welfare losses (Kang, Ye and

[30] I have learned greatly from some excellent resources in the U.S., such as MDRC's "In Search of a Match: A Guide for Helping Students Make Informed College Choices" and the College Board's Big Future program. Our research team carefully reviewed more than 200 Chinese websites and guidebooks that contained information about college entrance exams and college applications. I have identified the most reliable and useful information that later was synthesized in the guidebook.

[31] There are various online sources available to Chinese students, but most of them are unreliable and contain mistakes. It is not easy for students to find the reliable sources of information about college applications and to understand how to navigate the sources to find the information they need.

Ding, 2020) because Ningxia, as one of the poorest provinces, lacks high-quality colleges.

Intervention 1: Guidebook. With the assistance of the Ningxia Department of Education, I distributed the "How to Apply to College?" booklet to all the students in the treated schools through school administration. Students were informed that the guidebook was prepared by researchers at Peking University, the top college in China, and at Ningxia University, the top college in Ningxia. The guidebook is expected to help students gather information and facilitate their learning of the rules and principles necessary to make a knowledgeable decision for themselves.

Intervention 2: Guidebook and school workshop. To advance students' learning of the guidebook, I worked with local districts and high school leaders to plan and run school workshops. To minimize the quality variations in the workshops, I selected a group of very knowledgeable experts - the guidebook editors - to give the workshops using the same slides and scripts at each school. Workshops were announced one month ahead of time in the name of a joint research team from Peking University and Ningxia University. Each workshop lasted three hours and was moderated by a high-level school administrator. Figure C.3 shows sample pictures of the workshops, during which all the four "course" modules were covered in detail by the speakers and a Q&A session was included. We purposely distributed the booklet to students who attended the school workshop. About half of students who did not show up in the workshop did not receive the guidebook. Additionally, we provided students in the workshop access to online individualized advising, which will be discussed in Subsection 5.3.

4.2. School Level Randomization

The randomization was at the school level. As requested by the Ningxia Department of Education, I first randomly selected three cities out of the five prefecture cities in Ningxia. I implemented the experiment in all public high schools in these three cities, which resulted in 31 schools (out of the total 60 schools in Ningxia) in the experimental sample. I then created four strata for the three cities by dividing the capital city into two strata based on school quality.[32] Within

[32]The reason is that the most selective high schools concentrate in the capital city. School quality is measured using confidential school finance data in 2013, the latest year of the data I obtained from the China Ministry of Education.

each stratum, I randomly assigned three schools to receive the guidebook treatment, two schools to receive both the guidebook and the workshop, and the remaining three schools to not receive either treatment, serving as the control group (see a summary in Table B.1).[33]

Implementation and take-up. Of the total 32,834 high school graduates in 2016 in 31 public high schools, 11,408 students were in 12 control schools. In mid-June, before students submitted their college applications, 12,823 students in 12 schools were provided with the guidebook (T1). The guidebooks were sent directly to each treatment school. School administrators distributed them to individual students when they came back in school to receive their score reports.[34] Another 8,603 students in 7 schools were provided with both the guidebook and the workshop (T2).[35] Workshops were held during 22-24 June 2016, when students started to submit their college applications (the deadline was 27 June). All students in the workshop schools were informed one month ahead of time, and their parents were also invited to participate. Nevertheless, I was unfortunately not able to identify an accurate, individual-level take-up of the school workshops because schools failed to track the "treated" students (attendees) due to the lack of incentive and organizational capacity in these high schools. According to the number of booklets distributed to students, the take-up in T1 schools is 98% and approximately 42% of students in the T2 schools attended the workshop and received the guidebook (29%-56%, varying by school).

Summary statistics and validity. The summary statistics in Table B.6 indicates that the experimental sample is representative of the entire high school graduation cohort. Exceptions are that the experimental sample has a 0.11 s.d. higher average CEE score, a 6% lower minority student fraction, and a 7% higher rural student fraction. About 60% of students are from rural families, about 30% are minorities (mostly Muslims), and about 20% of college applicants have repeated the 12th grade at least once. The average college admissions rate is 84 percent. Students on average undermatch by attending colleges with lower-achieving peers than themselves.

Within the experimental sample, mean student characteristics differ slightly between groups

[33] The number slightly varies across strata due to rounding.

[34] Students can check their CEE scores online, but they are required to receive a formal printed report.

[35] I initially randomized eight schools for the workshop. One workshop was not held due to the ineffective school organization. I coded that school in T1. Results do not change if I drop this school from the analysis.

because the randomization used school-level finance data in 2013. T1 has more rural students, and relatedly, on average lower-achieving students. However, controlling for strata fixed effects, these three groups are balanced in observed characteristics for schools (using both the 2013 finance data that were used for randomization and the 2016 sample student data; see Table B.7) and for students (for both the whole sample and the high-achieving sample in 2016; see Table B.8).

4.3. Econometrics

I examine whether and how the interventions alter students' college choice behaviors as discussed in Subsection 3.2 and how the changes in college choice behaviors would affect admissions outcomes as described in Subsection 3.1.[36] I use the following linear regression to estimate the intent-to-treat effects (ITT):

$$Y_{ij} = \beta_0 + \beta_1 * T1(guidebook)_j + \beta_2 * T2(guidebook + workshop)_j + X_i * \gamma + \delta_s + \varepsilon_{ij} \quad (2)$$

where Y_i is the outcome of interest for student i in school j of randomized stratum s. $T1_j$ and $T2_j$ are indicator variables for school j receiving the guidebook treatment and the guidebook-workshop combination, respectively. T2 also includes a small proportion of students who received one-on-one advising, to be discussed in Subsection 5.3. δ_s are strata fixed effects. X_i includes a set of student characteristics, particularly a student's CEE score, to identify the "college choice" effect. I also control for demographics (gender, race, age, STEM/Non-STEM track, repeater) to account for group differences in college preferences. All standard errors are clustered at schools.

I address multiple hypothesis testing in several ways. The outcome measures closely follow the literature and are within the same family of practice domains. For example, the college admissions outcomes are from different yet highly correlated perspectives, which jointly provide a complete picture of college access and match. I primarily aggregate the outcome measures to several single indexes to minimize the potential multiple hypothesis testing bias. Additionally, I apply the method proposed by List, Shaikh and Xu (2016) to confirm the robustness of results.

Another issue of the cluster randomized experiment is the relatively small number of clusters (schools), which may result in incorrect statistical hypothesis tests (e.g., in *p*-values) based on

[36] The main college match measures were explored in Loyalka, Wu and Ye (2017), which motivated the development of the *Bright Future of China Project*.

large number asymptotic properties. I use randomization inference to assess whether the observed treatment effects are likely to have been observed by chance even if treatment had no effect (Heß, 2017). I report p-values from 1,000 permutations.

Since the take-up of T1 is more than twice that of T2 according to anecdotal evidence, the treatment-on-the-treated (TOT) effects would be of policy interest as well. To approximately compute the TOT effects, one can use a Wald estimator to rescale the ITT effects by the take-up probabilities. Based on the homogeneous treatment effect assumption, the approximates provide a sense of the results if we could scale-up the interventions through making the guidebook and workshop a mandatory part of the high school curriculum or counseling.

5. Results

5.1. Effects on College Application Behaviors

In developing the *Bright Future of China Project*, based on the structured four-step framework of college choice decision-making, I identified a set of core strategies for students to make informed college choices. I then provided treated students with these strategies using a guidebook or a guidebook-workshop combination. I expected that students would change their college choice behaviors; in particular, students' applications would be consistent with better understanding of the admissions policies and improved predictions of college admissions probabilities.

The expectation is correct. Table 3 shows that the interventions have substantially altered students' college choice behaviors.[37] Column (1) uses the single principal-component factor index to summarize the ITT effects on college application behaviors. The guidebook-workshop intervention statistically significantly and substantially improves college applications. Students in the guidebook-workshop treatment schools on average submit college applications with a 0.167 s.d. ($p<0.05$) higher quality index, a nearly 100 percent increase from the control group mean. Given that the take-up is about 40%, the TOT effect might be even larger. The guidebook alone also improves applications,

[37] I should note that the college application behaviors characterized in the data do not fully characterize how students could make their optimal choices, given that they could apply to more than 50 colleges and then 300 college-major options. Strategies and preferences are interrelated, so that students need to carefully consider all of them to construct their college and major application lists. Results in this subsection are very consistent with the expectations in designing the project, as well as numerous fieldwork observations and feedback not captured in the data.

but in an imprecise and smaller magnitude. In columns (2)-(7), I test the strategy and preference groups separately. Consistent with the descriptive results in Table 2 that the targeting strategies are the most important factors driving college match, both the guidebook and the guidebook-workshop interventions have statistically significantly and substantially improved students' use of targeting strategies with a more than 100 percent increase in the quality index.

Results in Table 4, which report estimates for each individual college choice behavior item, confirm that the effects are well aligned with focus of precise predictions in the intervention designs. Changes in targeting strategies are not from just one or two items by chance but are from improvements in all elements that are related to an optimal college application. The ITT effects show that students are more than 10 percent (3 to 4 percentage points) more likely to apply to a mix of reach, match, and safety colleges (column 7) and rank these colleges in a descending order of predicted admissions cutoffs (column 6). Though imprecisely estimated, students are also more likely to equate their CEE scores (indicated by the estimated gap in column 4) and more likely to apply to colleges in the institutional tier that match their CEE scores (column 5). Based on better predictions using historical data, they are also more than 20 percent more likely to apply to colleges without admissions data in the prior year (column 8). Taken together, these results consistently indicate that treated students have substantially improved their precise predictions.

In addition to helping students better understand and predict college admissions probabilities, the interventions have also largely shifted students from colleges in Ningxia or neighboring low-income regions to out-of-province colleges, especially in the economically developed regions. While both the guidebook and workshop present the same information regarding geographic preference, the differences in magnitude and statistical significance between the two treatment groups might be from the increased nudge and attention brought to students during the school workshop. The interventions do not significantly affect students' other strategic application behaviors, neither the general nudge advice nor applications to special programs. As hypothesized, students' preferences for tuition, admissions quota, and specific majors are also not impacted.

5.2. Effects on Admissions Outcomes

Table 5 presents results of ITT effects of the guidebook and workshop interventions on college access and match outcomes. Each column reports coefficient estimates from a separate OLS regression of Equation 2.[38] I find that both the guidebook and the guidebook-workshop combined interventions substantially improve college admissions. On the extensive margin, column (1) shows that offering guidebooks or school workshops causes students to be 2-3 percentage points more likely to be admitted to a college, although imprecisely estimated due to the small number of clusters. In Table B.9, I show that the interventions insignificantly increase college application by about 1 pp. Comparing the two estimates, the interventions have increased the college admission rate conditional on application by about 1-2 pp. Nevertheless, this increase is not statistically significant.

Results on the intensive margin of college match show that treated students on average are admitted to statistically significantly and substantially higher quality colleges. Column (2) of Table 5 shows that students who are offered, and potentially read the "How to Apply to College?" guidebook, are admitted to a college with a 0.094 s.d. ($p<0.001$) higher quality using the single college match index. If students remain unchanged in their college application behaviors, they would have to score 0.094 s.d. higher on the College Entrance Exam to be able to get into the same college. This result demonstrates that providing a "college application textbook" generates large improvements in student college access and match during a very short time period at a reasonably low cost (about $5).

The ITT effects of the guidebook-workshop combined intervention (T2) are very similar. Treated students, on average, are admitted to colleges with a 0.076 s.d. ($p<0.05$) higher college match index. Given the anecdotal evidence, the approximate TOT effects for a student who may have learned from both the guidebook and workshop (T2) might be two or three times larger than guidebook alone (T1). For example, using the Wald estimator, the rescaled TOT effect on college match index is about 0.18 s.d. (ranging from 0.15 to 0.23 s.d.). The results confirm that informing students on making precise predictions of college admissions probabilities is effective at helping

[38] Results are similar when I do not control for student demographic covariates or control for additional school covariates that are aggregated from student covariates.

students improve college match. Comparing with the rural-urban gap as reported in column (4) of Table B.3 (-0.176 s.d.), a fully implemented guidebook-workshop combined intervention, assuming treatment effect homogeneity, could close this poverty gap.

To check the robustness of defining college quality for those non-admitted, column (3) excludes students who are not admitted to college, and shows a smaller impact of the interventions. However, given that the interventions affect college admissions, this result is downward biased. Column (4) shows that treated students are 3-4 percentage points less likely to be admitted to undermatched colleges. Columns (5)-(9) show the itemized results of the college match measures, which are the principle-component factors of the summary index in column (2). Results show that the improvement in college match is quite stable using either within-province or national measures.

In Table B.9, I explore the treatment effects on additional outcomes. Results are mostly imprecisely estimated due to limited statistical power from the school-level randomization. There is suggestive evidence that the interventions increase college enrollment in the same year by decreasing the probability of repeating the 12th grade for another year.[39] The interventions also increase the share of students that are admitted to match/peer and overmatch/reach colleges.

5.3. Discussion

Effects on high achieving students. I find quite similar intervention effects on high achieving students. As shown in Table B.10, providing both guidebook and workshop to high achieving students who are eligible for selective college admissions based on their CEE score has similarly affected these students' use of targeting strategies and out-of-province college preferences. The impact of the guidebook only intervention is smaller and statistically insignificant. Table B.11 repeats the analysis on college admissions outcomes. Nearly all high achieving students, who are also highly motivated for college, apply to and are admitted by a college. Thus the interventions have a precisely zero effect on applications and admissions. This finding is different from that in the U.S. For example, the ECO project in Hoxby and Turner (2013) increased high-achieving, low-income students' college admissions by 12 percent. The reason for this difference is that

[39] Survey data show that students who choose to repeat are unsatisfied with either their CEE scores or college admissions results.

some high achieving American students may not apply to any college. Chinese students do apply for college. However, they may not know how to apply to an appropriate set of colleges due to problems of precision predictions of admissions chances. Consistently, I find clear evidence that both the guidebook and the guidebook-workshop combined interventions have statistically significant impacts on college match for high achieving students in both the single index and itemized measures. Being offered and potentially reading the guidebook increases college match index by 0.058 s.d. ($p<0.05$), holding CEE scores and demographics equal. Being offered both the guidebook and workshop increases college match index by 0.08 s.d. ($p<0.001$).

Heterogeneity in the treatment effects. Figure 3 summarizes the heterogeneous effects on college admissions; I also find similar, consistent heterogeneity in college choice behaviors. For the guidebook only intervention, the ITT effects are slightly larger for rural, female and minority students. For the guidebook-workshop combined intervention, female and non-minority students benefit more. These differences may result from differential take-up between groups. Lastly, the interventions do not have large impacts on repeaters. Repeaters already have at least one year's experience of college applications. They are more experienced and skilled in searching for and using the relevant information and strategic decision-making. Figure A.4 shows similar results among high achieving students. One exception is that high-achieving repeaters also benefit from the workshop, particularly from learning the strategies and skills to make more accurate predictions.

Note on the one-on-one advising. As mentioned earlier, a small number of students received one-on-one advising. The individualized advising was not randomized at the student level since it was in development phase. Students who attended one of the five school workshops (randomly chosen from the total seven T2 schools) were provided opportunities (vouchers) to receive individualized advising from experts on our research team. The overall take-up is 1.5% (N=119).[40] The individualized advising was implemented through the two largest and popular online chat Apps in China (similar to iMessage) using text, picture, and video. Students who self-selected to sign up for assistance were then assigned by the administrative assistants to one of the six core advisors. The

[40]More than 800 users contacted us, but the screening process, based on school and student IDs, largely decreased the eventual take-up.

advisors helped students with all the four steps that are structured in the guidebook. Particularly, the advisors directly helped the students to predict college admissions chances, based on which they provided personalized, detailed guidance on selecting colleges to apply to. Figure A.5 shows the real conversations about predicting college admissions to select reach colleges to apply to between one treated student and one advisor.

In the absence of individual-level randomization, it is difficult to estimate the causal impact of the one-on-one advising. Figure 4 presents the distribution of college peer median scores between students who actually received one-on-one advising and students in the control group. The figure clearly shows that, with few exceptions - particularly students who did not apply to any college because they chose to retake the CEE the next year - most students who received the individualized advising were admitted to their match or even reach colleges.[41] Given the small number of students receiving personalized advising, I do not expect that the estimated impacts of the guidebook-workshop combination are largely driven by these students. In Table B.12, I estimate the treatment effects by the five schools with the invitations (voucher) and the two schools without invitations. Results are almost the same.

General equilibrium effects. One concern regarding the estimated intervention impacts on college admissions outcomes is that about one-third of the populations of applicants were treated. The admissions outcomes of the control group were also likely to be impacted that the estimated intervention impacts on admissions might be upward biased. I address this question by projecting the changes in admissions outcomes based on the intervention impacts on college choice behaviors (reported in Table 3) and the estimated correlation coefficients between college choice behaviors and college admissions outcomes using the untreated sample (reported in Table 2). The projected increases in college match index by the guidebook only and the guidebook-workshop combined interventions are 0.033 s.d. and 0.029 s.d., which are close to the estimated ITT effects in column (3) of Table 5 (0.030 s.d. and 0.029 s.d.).

[41]Treated students were not all shifted to the top of the outcome distribution because the intervention did not focus on the single task of increasing admitted college quality. Instead, during the personalized advising, students' multidimensional preferences were fully considered. One example is the preference for specific majors. If students are admitted to a reach college, they are more likely to be assigned to less popular majors for which they have low interest.

6. Summary

In this paper, I study college choice behaviors and admissions outcomes in a centralized college admissions system. Using administrative data of college applications and admissions from one of the poorest provinces in China, I document that the student-college academic undermatch is prevalent in centralized college admissions. I find descriptive evidence that the undermatched college choices occur because students do not appropriately use college application strategies, especially the strategies that make precise predictions of college admission probabilities. I then conducted a large-scale randomized experiment to examine what works in improving college choices and admissions for low-income students. The experimental evidence shows that informing students on making precise predictions of college admissions probabilities is effective in improving college access and match for low-income students.

This paper makes the first-step attempt to improve college access and match by changing college choice behaviors among low-income students in centralized admissions. The results build a stage for improving relevant policy designs. Low-income and other disadvantaged students lack the ability to make optimal college-going decisions, especially in understanding the admissions mechanisms and conducting intensive data analytics. The *ex ante* expectation of this project was that the prediction and targeting strategies are the key components of the knowledge in college choice and application. This is particularly true in the centralized admissions systems that reward strategy and sophistication. The experimental evidence in this paper provides the proof of effectiveness of behaviorally-designed college choice and application interventions. However, these individualized, data-based predictions and targeting strategies require intensive learning and data analysis, which limits the potential of scale-up. Innovative scalable policy solutions are needed to simplify the instruction and learning process.

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Figures

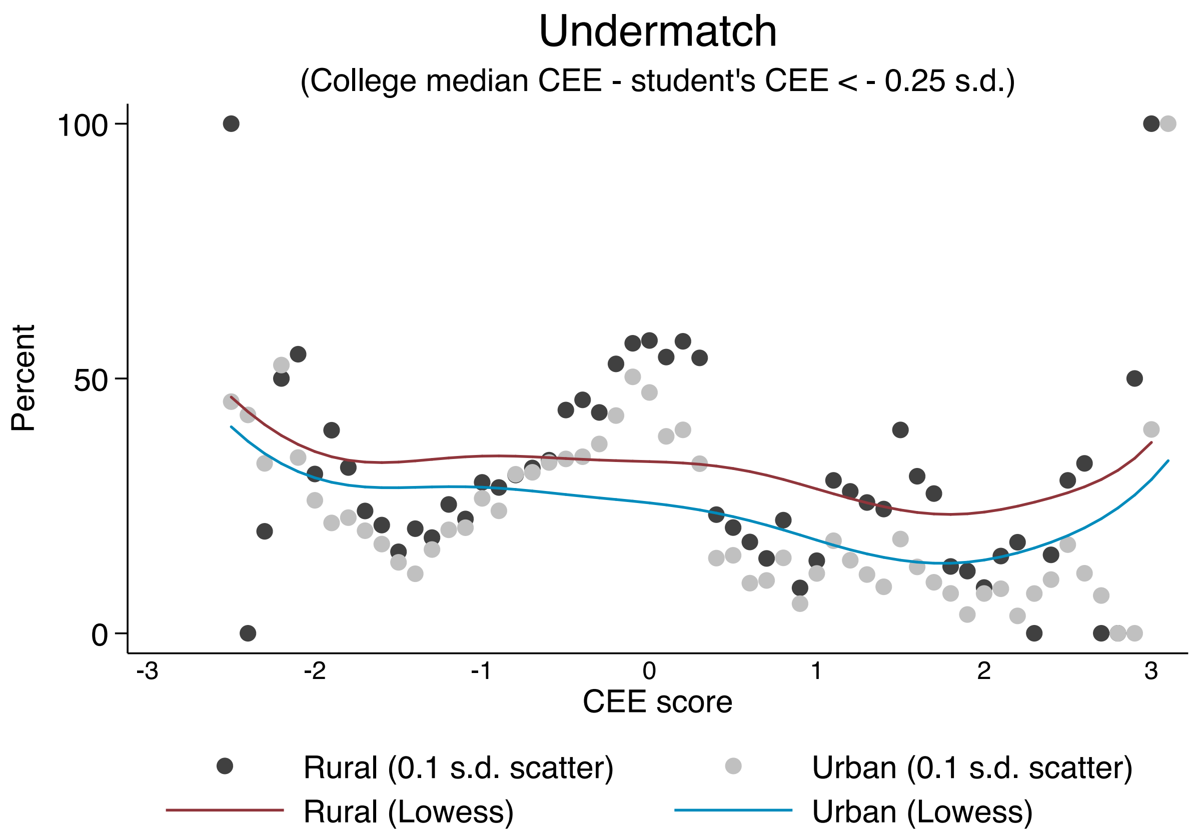


Figure 1: Rural-urban gap in academic undermatch

Notes: This figure plots locally weighted regression lines of academic undermatch rates between rural and urban students on the x-axis of students' CEE score (standardized). Each dot represents the average undermatch rate for a 0.1 s.d. bin. Undermatch is defined as a student being admitted by a college with median CEE score 0.25 s.d. lower than her own CEE score or not being admitted by any college. The sample includes the universe of the untreated sample (including both the control group of the randomization sample and those not in the randomization sample) of the 2016 cohort of high school graduates in Ningxia, China.

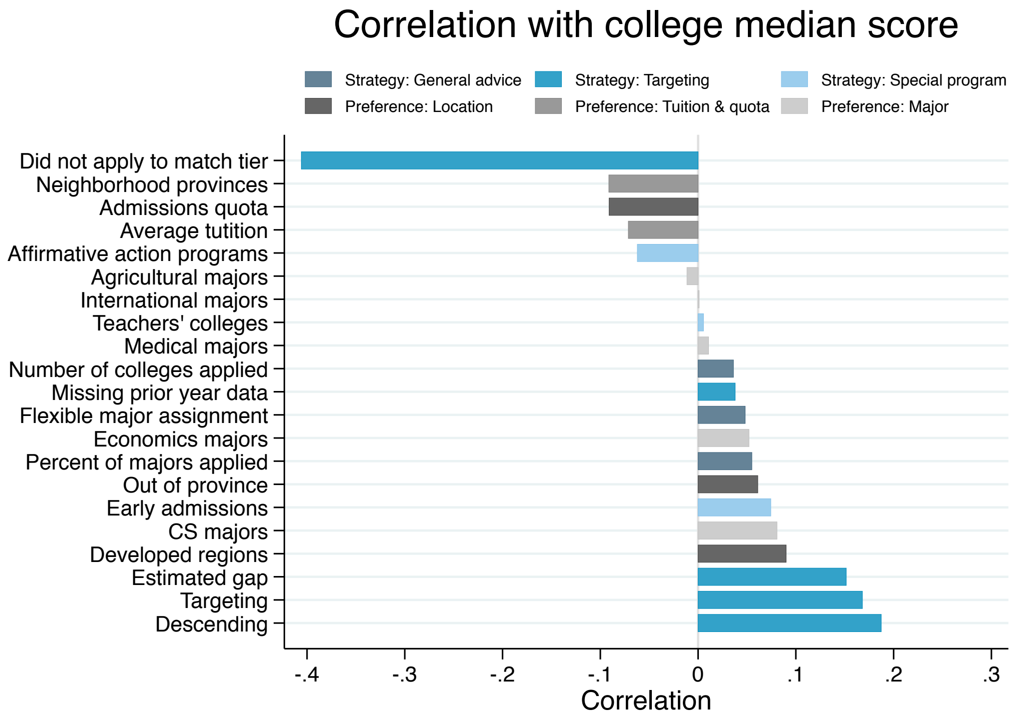
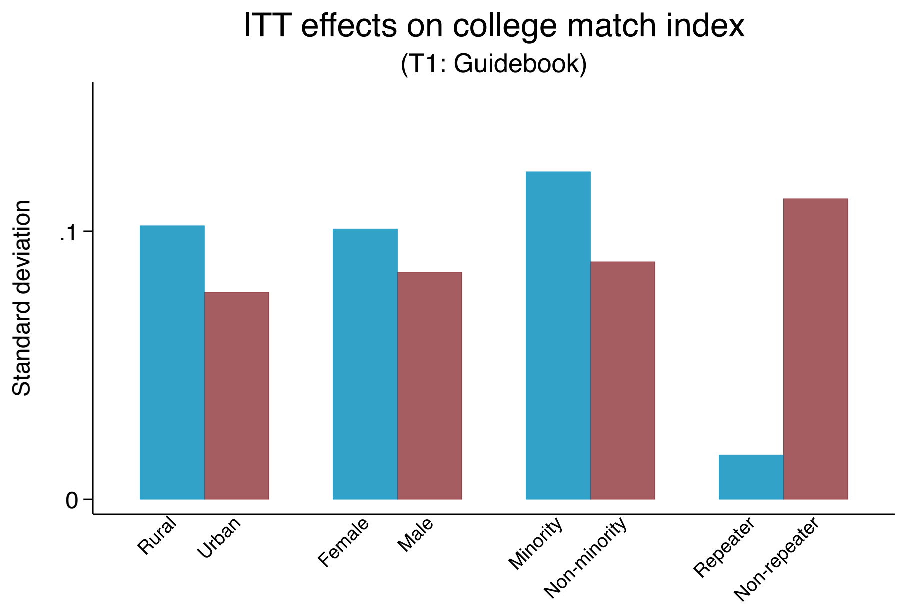
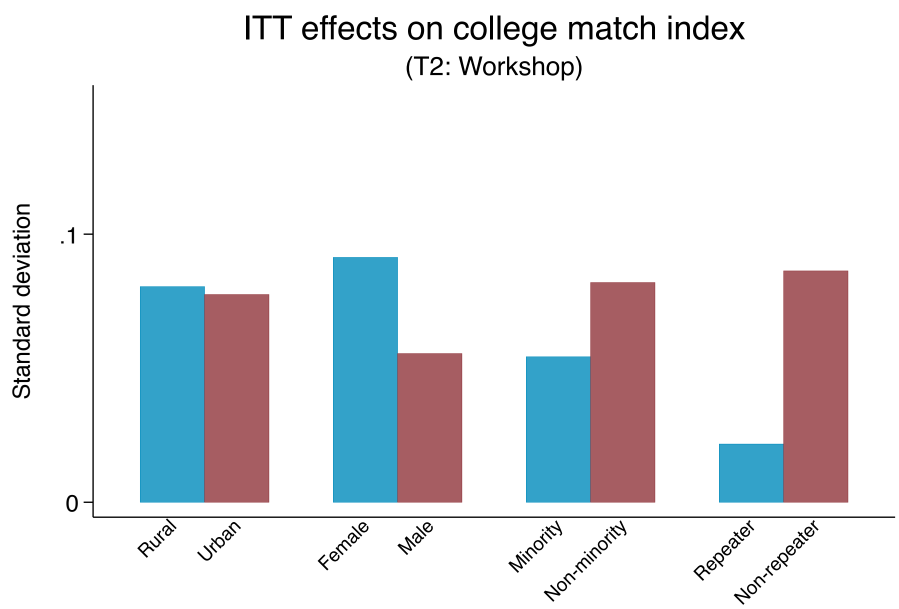


Figure 2: Correlates of college choices and admissions outcomes

Notes: This figure plots pairwise correlations between college match outcome (college median CEE score after adjusting for one's own CEE score and demographics) and several individual-level college choices and applications characteristics (strategies and preferences), as described in Appendix Subsection C.1.



(a) T1: Guidebook



(b) T2: Workshop (based on guidebook)

Figure 3: Heterogeneity in the ITT effects

Notes: This figure plots heterogeneous ITT effects of the interventions on college median score from the OLS regression Equation 2 using each subsample (e.g., rural students vs. urban students) separately.

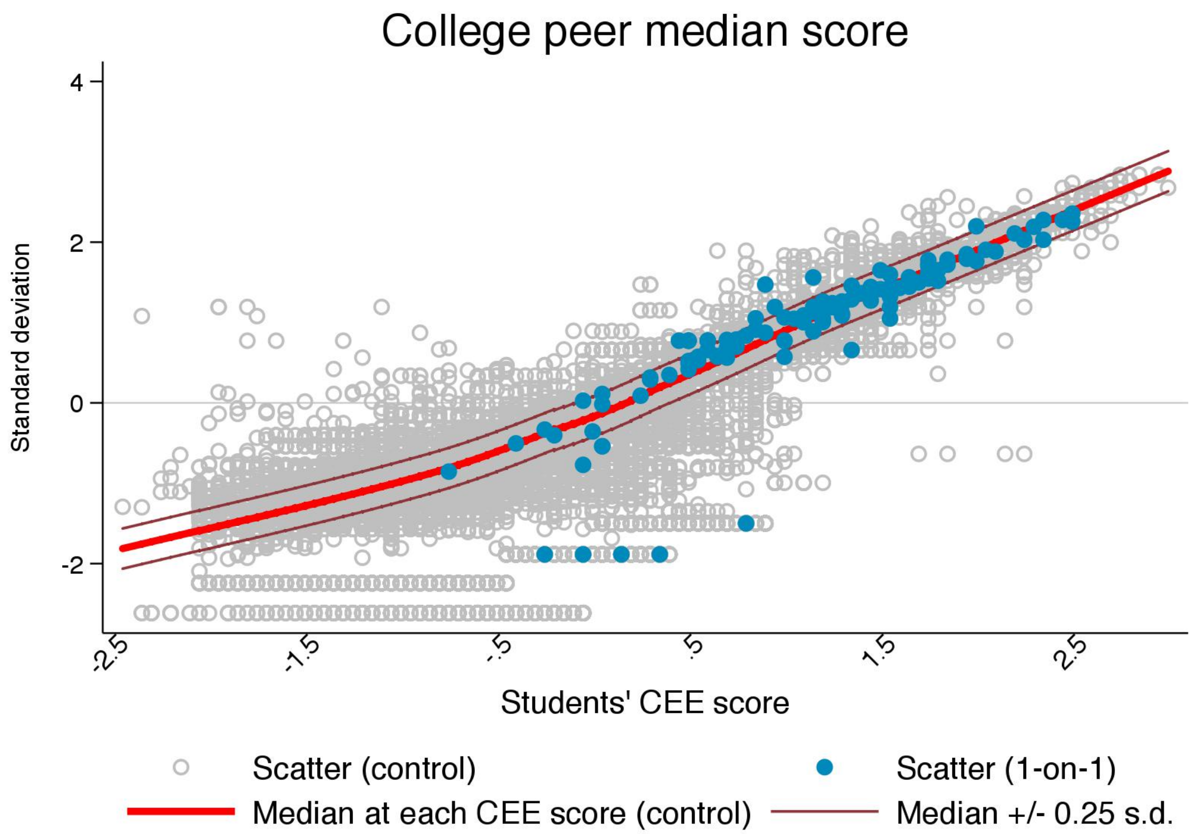


Figure 4: Distributions of college peer median score between students received 1-on-1 advising and students in the control group in 2016

Notes: This figure plots the distribution of college peer median score between students who actually received 1-on-1 advising and students in the control group in 2016. For better illustration, each scatter summarizes students with a bin of 0.05 s.d. CEE score. The red line shows a locally weighted average of the outcome, and the maroon lines show the lower and upper borders of the match college range (0.25 s.d.). The bottom scatters indicate the tier-track specific lowest scores for those who are not admitted to a college.

Tables

Table 1: Extent of academic undermatch: College access vs. college choice

	College quality quartiles (enrolled in) (N=31,777)					Percent Undermatch		Percent Overmatch
CEE quartiles (access to)	1st Quartile (Highest)	2nd Quartile	3rd Quartile	4the Quartile (Lowest)	No college	(0.25 s.d.)	(5 pctl)	(0.25 s.d.)
1st Quartile (Highest)	7,450 (90.3)	740 (9.0)	13 (0.2)	1 (0.0)	50 (0.6)	15.0	20.3	4.1
2nd Quartile	1,031 (12.5)	4,837 (58.6)	618 (7.5)	179 (2.2)	1,593 (19.3)	29.1	35.1	7.8
3rd Quartile	13 (0.2)	736 (9.4)	3,714 (47.5)	1,379 (17.6)	1,977 (25.3)	45.9	52.7	4.3
4th Quartile (Lowest)	8 (0.1)	64 (0.9)	1,038 (13.9)	4,955 (66.6)	1,381 (18.6)	25.2	26.1	33.3
Total						28.6	33.5	12.0

Notes: This table reports the joint distribution of students' College Entrance Exam (CEE) score and their admitted colleges' quality (measured by college median CEE score), using the universe of the untreated sample (including both the control group of the randomization sample and those not in the randomization sample) of the 2016 cohort of high school graduates in Ningxia, China. Each cell contains the number of students and the row percentage (in parentheses). The last three columns report the undermatch and overmatch percents by student CEE score quartile, using 5 percentile and 0.25 standard deviation as cutoffs, respectively. **Undermatch** is when a student's own CEE score is 0.25 standard deviation (or 5 rank percentile) higher than here admitted college's median CEE score, or a student was not admitted to any colleges. **Overmatch** is when a student's own CEE score is 0.25 standard deviation lower than her admitted college's median CEE score.

Table 2: College choices and the poverty gap in admissions outcomes

		Outcome: Index of college match						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rural-urban gap		-0.176***	-0.123***	-0.074***	-0.069***	-0.035***	-0.035***	-0.031***
(β_1)		(0.026)	(0.018)	(0.012)	(0.012)	(0.009)	(0.009)	(0.009)
Strategy	General advice				0.030***	0.006	0.006	0.004
					(0.007)	(0.007)	(0.007)	(0.007)
Strategy	Targeting					0.218***	0.218***	0.217***
						(0.011)	(0.011)	(0.011)
Strategy	Special programs						-0.003	-0.007
							(0.005)	(0.005)
Preference	Tuition & quota							0.057***
								(0.007)
Preference	Location							0.079***
								(0.004)
Preference	Major							-0.006
								(0.004)
School FE		No	No	Yes	Yes	Yes	Yes	Yes
Observations		31,777	28,806	28,806	28,806	28,806	28,806	28,806
R-squared		0.589	0.657	0.665	0.666	0.706	0.706	0.710

Notes: This table reports the OLS regression (Equation 1) results of the correlations between college application behaviors and college match index, using data from those who submitted college applications in the untreated sample in 2016. Application behaviors are constructed using the full applications data, as described in Appendix Subsection C.1. Column (1) shows the rural-urban gap in college admissions using the full untreated sample (same as in column (3) of Panel C in Table B.3). Column (2) replicates the same analysis using the applicant sample. Column (3) controls for high school fixed effects (results are similar using class fixed effects). Columns (4)-(7) add the strategy and preference measures (principal component factor indices) stepwise. All regressions include a student's CEE score and other demographic covariates. Standard errors in parentheses are clustered at high school level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Estimates from regressions without school fixed effects in columns (4)-(7) are -0.113, -0.067, -0.067, and -0.054, all statistically significant at 1%.

Table 3: ITT effects on college choice behaviors: Principal-component factors

	Index	Strategy			Preference		
		General	Targeting	Special programs	Tuition & quota	Location	Major
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Control mean	0.171	0.066	0.087	0.299	-0.068	0.130	0.035
Control sd	[0.977]	[0.952]	[1.034]	[1.020]	[1.035]	[0.998]	[1.049]
T1 (guidebook)	0.091	0.071	0.107**	-0.099	-0.024	0.124	0.009
	(0.195)	(0.317)	(0.020)	(0.145)	(0.766)	(0.113)	(0.870)
T2 (workshop)	0.167**	0.040	0.091*	0.076	-0.114	0.208**	0.063
	(0.036)	(0.615)	(0.082)	(0.369)	(0.185)	(0.019)	(0.328)
N	29,591	29,591	29,591	29,591	29,591	29,591	29,591

Notes: This table reports the OLS regression (Equation 2) results of the ITT effects of the guidebook and workshop interventions in 2016 on college choice behaviors. Sample includes all the students in the randomization sample and submitted their college applications. We use principal component factor analysis to create a single index for each strategy and preference group, and an index for all (in column 1). Strategies and preferences are constructed using college application data, as described in Appendix Subsection C.1. All regressions control for student-level covariates (CEE score and demographics) and strata fixed effects. Randomization inference p-values from 1,000 permutations are in parentheses (clustered at high school level). * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 4: ITT effects on college choice behaviors: Itemized results

	General advice			Targeting				
	# College	% major (%)	% flexible (%)	Estimated gap (=1)	No match tier (=1)	Descending (=1)	Targeting (=1)	Missing prior data (=1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Control mean	7.898	70.723	70.196	0.384	0.238	0.338	0.366	0.018
Control sd	[4.490]	[22.626]	[36.366]	[0.486]	[0.426]	[0.473]	[0.482]	[0.133]
T1 (guidebook)	-0.655*	1.078	2.778	0.020**	-0.033	0.044**	0.042**	0.004
	(0.053)	(0.347)	(0.371)	(0.044)	(0.179)	(0.011)	(0.040)	(0.131)
T2 (workshop)	0.116	1.065	0.756	0.015	-0.034	0.035*	0.034*	0.004
	(0.776)	(0.387)	(0.849)	(0.182)	(0.192)	(0.058)	(0.096)	(0.190)

	Special programs			Tuition and quota	
	AA (%)	Early (%)	Teachers (%)	Tuition (in 1000s)	Quota
	(1)	(2)	(3)	(4)	(5)
Control mean	0.275	0.197	3.788	6.233	655.006
Control sd	[0.446]	[0.398]	[9.461]	[3.125]	[566.357]
T1 (guidebook)	-0.031*	0.001	1.223	-0.187	-58.934
	(0.077)	(0.958)	(0.111)	(0.326)	(0.226)
T2 (workshop)	-0.004	0.029	-0.963	0.058	-86.557
	(0.862)	(0.235)	(0.363)	(0.777)	(0.132)

	Location			Major				
	Out of province (%)	Developed regions (%)	Neighborhood (%)	Economics (%)	Agriculture (%)	CS (%)	International (%)	Medical (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Control mean	40.258	7.806	51.936	23.341	1.246	2.947	1.917	11.656
Control sd	[31.967]	[14.795]	[35.252]	[20.877]	[4.440]	[5.710]	[4.259]	[20.343]
T1 (guidebook)	3.195	1.151	-4.346	-0.458	-0.017	0.361	-0.077	-1.701
	(0.299)	(0.196)	(-0.167)	(0.627)	(0.898)	(0.145)	(0.609)	(0.124)
T2 (workshop)	5.209	1.977**	-7.186**	1.201	-0.141	0.516*	0.124	-1.078
	(0.128)	(0.029)	(0.047)	(0.360)	(0.404)	(0.079)	(0.470)	(0.437)

Notes: This table reports the OLS regression (Equation 2) results of the ITT effects of the guidebook and workshop interventions in 2016 on college choice behaviors (detailed items). Strategies and preferences are constructed using college application data, as described in Appendix Subsection C.1. Sample includes all the students in the randomization sample and submitted their college applications. All regressions control for student-level covariates (CEE score and demographics) and strata fixed effects. Randomization inference p-values from 1,000 permutations are in parentheses (clustered at high school level). * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 5: ITT effects on college access and match outcomes

	Main outcomes				Outcomes in Index (column 2)				
	Admission	Index	Index*	Undermatch	College median	College mean	College min	Quality	Ranking
	(=1)	(s.d.)	(s.d.)	(=1)	(s.d.)	(s.d.)	(s.d.)	(s.d.)	(pctl)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Control mean	0.846	0.182	0.263	0.296	0.052	0.068	-0.688	-0.151	55.835
Control s.d.	[0.361]	[0.991]	[0.902]	[0.457]	[1.142]	[1.115]	[1.333]	[1.872]	[34.365]
T1 (guidebook)	0.032*	0.094***	0.030*	-0.040**	0.089**	0.083**	0.171***	0.181**	2.456**
	(0.076)	(0.009)	(0.075)	(0.033)	(0.017)	(0.020)	(0.000)	(0.023)	(0.029)
T2 (workshop)	0.024	0.076**	0.029	-0.026	0.071*	0.067*	0.118**	0.156*	2.324**
	(0.276)	(0.044)	(0.134)	(0.231)	(0.088)	(0.090)	(0.040)	(0.075)	(0.045)
N	32,834	32,834	27,657	32,834	32,834	32,834	32,834	32,834	32.834

Notes: This table reports the OLS regression (Equation 2) results of the ITT effects of the guidebook and workshop interventions in 2016 on a family of college access and match outcomes. **Admission** denotes whether a student was admitted to college. **Index** measures college match, using principal component factor analysis based the five continuous outcomes in columns (5)-(9). **Index*** excludes students who were not admitted to college. **Undermatch** is when a student's own CEE score is 0.25 standard deviation higher than here admitted college's median CEE score, or a student was not admitted to any colleges. **College median/mean/min scores** are constructed using all the admissions data in Ningxia in 2016. **Quality (standardized)** measures college quality using national data on college (admissions scores, inputs and employment data) from 1996-2017, and **Ranking** is the corresponding ranking percentile. All regressions control for student-level covariates (CEE score and demographics) and strata fixed effects. Randomization inference p-values from 1,000 permutations are in parentheses (clustered at high school level). * significant at 10%, ** significant at 5%, *** significant at 1%.

A. Appendix figures

Figure A.1: Location of Ningxia

Notes: Ningxia, officially the Ningxia Hui Autonomous Region, has the third smallest GDP in China with Muslims forming more than 38% of its population. Most of the region is desert, making Ningxia one of the poorest provinces in northwestern China. In 2017, the annual per capita disposable (after tax) income of urban residents is about $4,200 (national average: $5,600), and that of rural residents is $1,650 (national average: $2,060). About 800,000 of its 6 million population are under the poverty line that earn less than $1 a day.

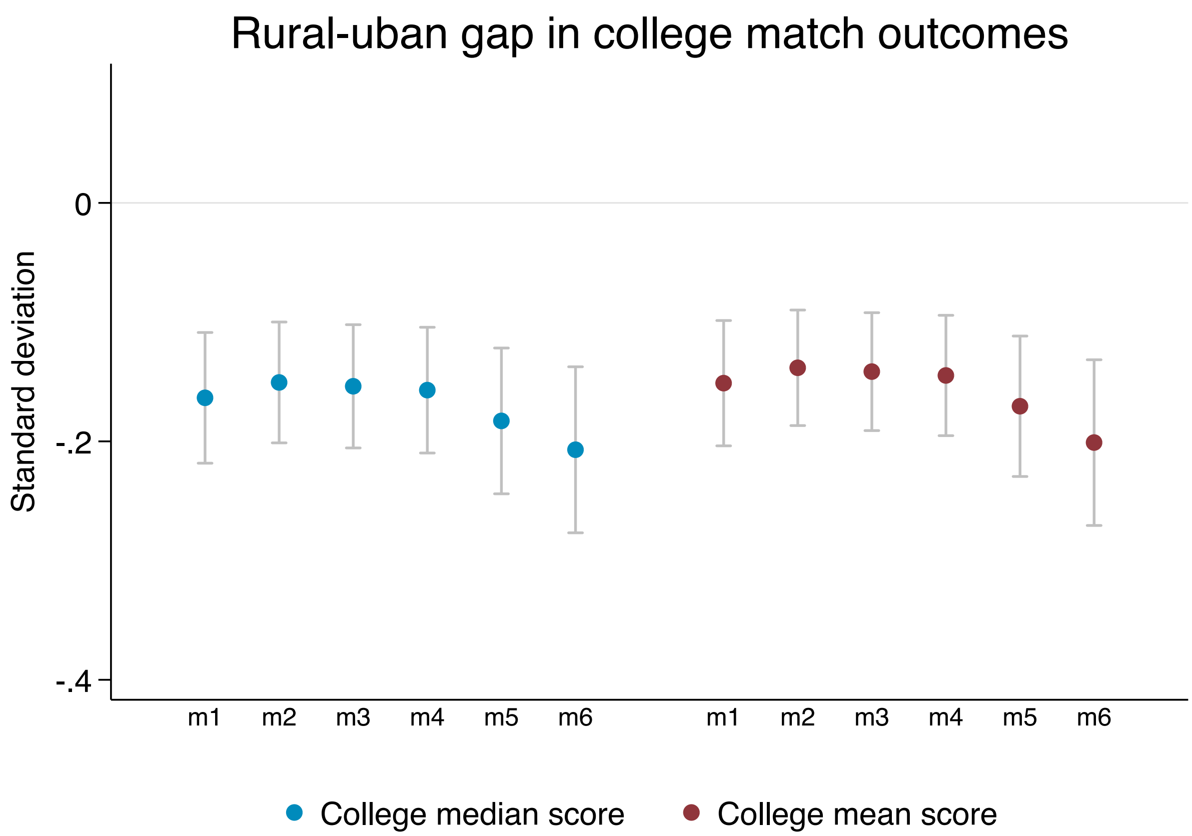


Figure A.2: Testing the sensitivity of different college quality measures

Notes: This figure shows the consistency of the estimates using different college quality measures for students who were not admitted to any college. Results of m1 correspond to Panel D of Table B.3 that controls for a student's CEE score and her demographic covariates. We assign the value of tier-track specific lowest college median/mean score minus 0.2 s.d. as the college median/mean score to students who are not admitted. From m2 to m5, we vary the threshold value: 0, 0.05 s.d., 0.1 s.d., and 0.5 s.d.; and in m6, we assign the lowest college median/mean score (not tier-track specific) to those students. All results (including those in the next sections, and those using other measures of the non-admitted students) remain very stable.

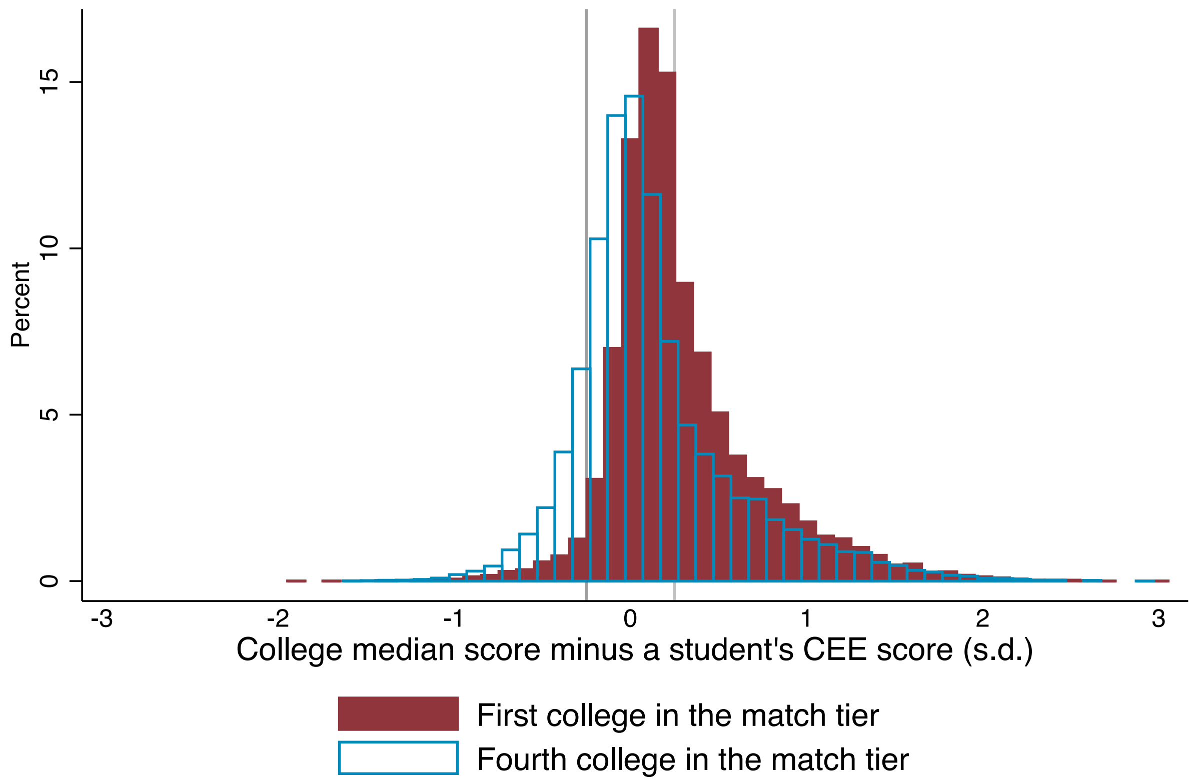
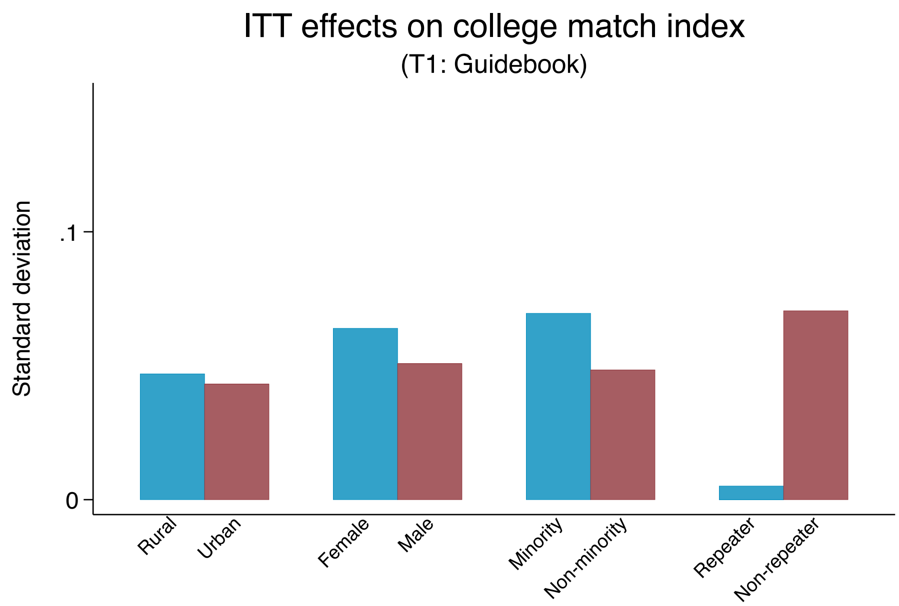
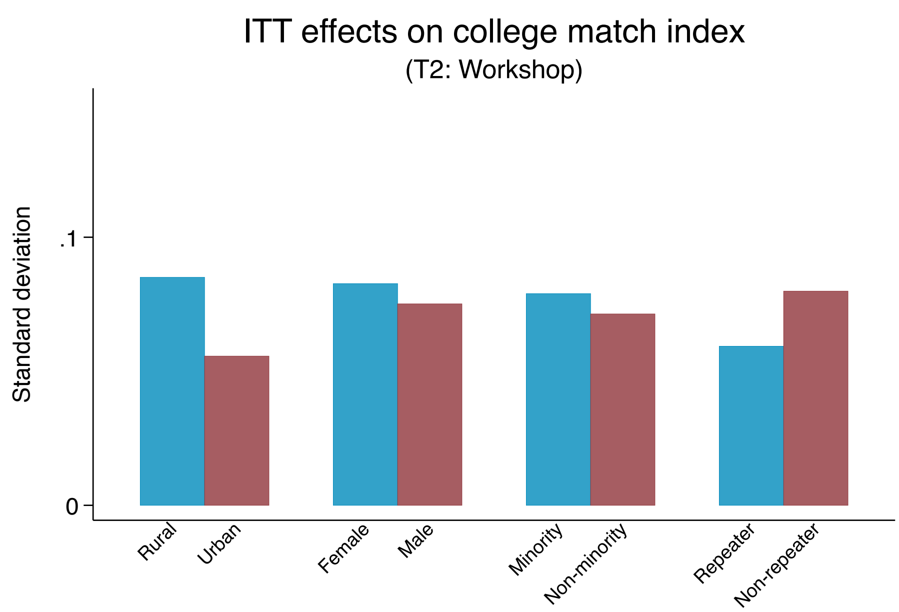


Figure A.3: Distribution of the distance of college median score and a student's own score

Notes: This figure shows the distribution of students' applications using the full application data.The X axis shows the distance of college median score and a student's own score. We separately present the distributions for students' first choice and fourth (last) choice in the match tier. **The match tier** indicates the highest possible selectivity tier that one student qualifies for based on her CEE score, which should be her primarily targeting tier. Two vertical gray lines indicate the boundary of match range (0.25 s.d. from zero).



(a) T1: Guidebook



(b) T2: Workshop

Figure A.4: Heterogeneity in the ITT effects: High achieving students

Notes: This figure plots heterogeneous ITT effects among high-achieving students of the interventions on college median score from the OLS regression Equation 2, but with each subsample (e.g., rural students vs. urban students) separately.

(a) Ajusting the reach college choice

(b) Admitted to the reach college

Figure A.5: Example of the online individualized advising in 2016

Notes: This figure shows a typical case of our 1-on-1 advising. In Panel A, the student asked whether Shandong University was beyond the range of "reach college" to apply to. The advisor asked the student to do the CEE score equating and asked for the scores in the past three years (564, 588, 588). After reviewing the admissions data, the advisor replied that it was appropriate to list Shandong University as her first choice. In Panel B, the student sent a message after about one month that "Thank you for your advising. I have been admitted to Shandong University." The conversations were at QQ, one of the two largest chat forms in China.

B. Appendix tables

Table B.1: Experimental design

Question	What works in improving college access and match?				
Sample	All 32,834 students in 31 public high schools in three cities				
Randomization	School level within strata				
Groups	Intervention	Randomization unit (schools)	Students	Take-up	Estimation
Control	No	12	11,408		
Treatment 1	Guidebook	12	12,823	Nearly 100%	ITT
Treatment 2	School workshop	7	8,603	Around 30-50%	ITT
Treatment 3	1-on-1 advising	5	6,025	1.5%	TOT

Notes: This table shows the experimental design of the *Bright Future of China Project* in Ningxia in 2016. The primary randomization is between the control group and the first two treatment groups. 1-on-1 advising in 2016 was not randomized at student level that we provided access to advising to students who attended the workshop in 5 of the 7 school workshops. Take-up rates for guidebook and school workshop in 2016 are from anecdotal evidence (school survey and field observations).

Table B.2: Measures of undermatch: Varying thresholds

	% undermatch							
	Including not admitted students				Excluding not admitted students			
CEE quartiles	0.05 s.d.	0.15 s.d.	0.25 s.d.	0.35 s.d.	0.05 s.d.	0.15 s.d.	0.25 s.d.	0.35 s.d.
1st Quartile (Highest)	45.1	25.7	15.0	9.4	44.7	25.3	14.5	8.8
2nd Quartile	45.9	33.5	29.1	27.4	33.0	17.6	12.1	10.1
3rd Quartile	63.5	53.1	45.9	41.8	51.1	37.2	27.6	22.1
4th Quartile (Lowest)	35.7	29.4	25.2	22.5	21.1	13.3	8.1	4.8
Total	47.6	35.3	28.6	25.1	37.9	23.3	15.3	11.1

Notes: This table shows the distribution of undermatch in different student CEE score quartiles along with varying thresholds. Even using a very conservative threshold (0.35 standard deviation above the college median CEE score) to define undermatch and focusing on the selected sample of students who were already admitted to college, there is still a substantial proportion of students were admitted to academically undermatched colleges.

Table B.3: Poverty gap in college access and match

	Admission (=1) (1)	Index (s.d.) (2)	Index* (s.d.) (3)	Undermatch (=1) (4)
Urban mean	0.879	0.173	0.153	0.231
	[0.326]	[1.008]	[1.032]	[0.422]
		A. No controls		
Rural-urban gap	-0.065***	-0.267**	-0.215	0.098***
(β_1)	(0.015)	(0.134)	(0.169)	(0.016)
		B. Control for CEE score		
Rural-urban gap	-0.055***	-0.161***	-0.088***	0.092***
(β_1)	(0.010)	(0.025)	(0.018)	(0.011)
		C. Control for CEE score and demographics		
Rural-urban gap	-0.067***	-0.176***	-0.079***	0.097***
(β_1)	(0.011)	(0.026)	(0.014)	(0.012)
		D. Control for CEE score, demographics, and class fixed effects		
Rural-urban gap	-0.043***	-0.099***	-0.034***	0.058***
(β_1)	(0.008)	(0.015)	(0.008)	(0.008)
N	31,777	31,777	26,776	31,777

Notes: This table reports the OLS regression (Equation 1) results of the rural-urban gap in various college access and match outcomes, using the universe of the untreated sample in 2016. The top two rows report mean and standard deviation (in square brackets) of each outcome variable for urban students. Each cell in Panels A-D is from a separate regression, showing the coefficient on the indicator of "rural *hukou* residence" (β_1). Column (3) only includes students who were admitted to a college. **Student-level demographics** include indicators of female, minority, repeater, and STEM track, and age by June 7, 2016 (=1 if at least 18 years old). Standard errors in parentheses are clustered at high school level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.4: Rural-urban gap in college access and match: Itemized outcomes of the index measure

	College median (s.d.) (1)	College mean (s.d.) (2)	Coll min (s.d.) (3)	Quality (s.d.) (4)	Ranking (pctl) (5)
Urban mean	0.017	0.026	-0.599	-0.111	53.872
	[1.192]	[1.172]	[1.362]	[1.758]	[33.252]
		A. No controls			
Rural-urban gap	-0.284*	-0.271*	-0.400**	-0.465**	-8.151*
(β_1)	(0.160)	(0.159)	(0.161)	(0.202)	(4.548)
		B. Control for CEE score			
Rural-urban gap	-0.153***	-0.141***	-0.278***	-0.314***	-4.598***
(β_1)	(0.025)	(0.024)	(0.040)	(0.055)	(0.981)
		C. Control for CEE score and demographics			
Rural-urban gap	-0.171***	-0.158***	-0.272***	-0.358***	-5.305***
(β_1)	(0.027)	(0.026)	(0.038)	(0.057)	(0.912)
		D. Control for CEE score, demographics, and class fixed effects			
Rural-urban gap	-0.099***	-0.090***	-0.144***	-0.210***	-2.986***
(β_1)	(0.016)	(0.015)	(0.023)	(0.033)	(0.480)
N	31,777	31,777	31,777	31,777	31,777

Notes: This table reports the OLS regression (Equation 1) results of the rural-urban gap in college match outcomes (as being summarized in the single index), using the universe of the untreated sample in 2016. The top two rows report mean and standard deviation (in square brackets) of each outcome variable for urban students. Each cell in Panels A-D is from a separate regression, showing the coefficient on the indicator of "rural *hukou* residence" (β_1). Student-level demographics include indicators of female, minority, repeater, and STEM track, and age by June 7, 2016 (=1 if at least 18 years old). **College median/mean/min scores** are constructed using all the admissions data in Ningxia in 2016. **Quality (standardized)** measures college quality using national data on college (admissions scores, inputs and employment data) from 1996-2017, and **Ranking** is the corresponding ranking percentile. Standard errors in parentheses are clustered at high school level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.5: Rural-urban gap in college access and match: Additional outcomes

	Application (=1) (1)	Enrollment in 2016 (=1) (2)	Repeating in 2017 (=1) (3)	Match (=1) (4)	Overmatch (=1) (5)
Urban mean	0.923	0.813	0.162	0.646	0.123
	[0.267]	[0.390]	[0.368]	[0.478]	[0.329]
			A. No controls		
Rural-urban gap	-0.029**	-0.100***	0.092***	-0.092***	-0.006
	(0.013)	(0.020)	(0.017)	(0.028)	(0.016)
			B. Control for CEE score		
Rural-urban gap	-0.021**	-0.087***	0.085***	-0.070***	-0.022**
	(0.009)	(0.011)	(0.013)	(0.012)	(0.010)
			C. Control for CEE score and demographics		
Rural-urban gap	-0.037***	-0.097***	0.096***	-0.075***	-0.022**
	(0.009)	(0.014)	(0.015)	(0.011)	(0.009)
			D. Control for CEE score, demographics, and class fixed effects		
Rural-urban gap	-0.021***	-0.053***	0.046***	-0.047***	-0.011***
	(0.006)	(0.008)	(0.008)	(0.009)	(0.004)
N	31,777	31,777	31,777	31,777	31,777

Notes: This table reports the OLS regression (Equation 1) results of the rural-urban gap in additional college access and match outcomes, using the universe of the untreated sample in 2016. The top two rows report mean and standard deviation (in square brackets) of each outcome variable for urban students. Each cell in Panels A-D is from a separate regression, showing the coefficient on the indicator of "rural *hukou* residence" (β_1). Student-level demographics include indicators of female, minority, repeater, and STEM track, and age by June 7, 2016 (=1 if at least 18 years old). **Enrollment in 2016** denotes students who received college admissions and did not repeat in 2017 (we do not have data from colleges about their actual enrollment status). **Repeating in 2017** denotes students who took CEE in 2016 and in 2017. **Match** indicates that a student's admitted college median score is within 0.25 s.d. radius of her own CEE score. Standard errors in parentheses are clustered at high school level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.6: Sample description: 2016 RCT

	All (1)	Not in RCT sample (2)	RCT sample (3)	Control (4)	T1 (5)	T2 (6)
Schools	60	29	31	12	12	7
Students	56,172	23,338	32,834	11,408	12,823	8,603
Rural	0.59	0.55	0.62	0.56	0.71	0.57
Female	0.55	0.55	0.54	0.53	0.56	0.54
Minority	0.31	0.34	0.28	0.38	0.24	0.21
Age (>=18)	0.87	0.86	0.87	0.84	0.90	0.86
STEM	0.67	0.65	0.68	0.70	0.66	0.69
Repeater	0.19	0.18	0.20	0.15	0.25	0.19
CEE score	0.09	0.03	0.14	0.36	-0.07	0.15
Admitted	0.84	0.84	0.84	0.85	0.84	0.84
College median score	-0.17	-0.21	-0.15	0.05	-0.34	-0.13

Notes: This table describes the sample in the 2016 program. Randomization is at school-level within strata. The descriptive statistics do not account for between-strata differences.

Table B.7: Balance checks: 2016 RCT

	All students			High achieving students		
	Control	T1	T2	Control	T1	T2
	(1)	(2)	(3)	(4)	(5)	(6)
A. Student-level results using student data in 2016						
Rural	0.556	-0.001	-0.133	0.650	-0.218	-0.294
	[0.497]	(0.997)	(0.282)	[0.477]	(0.268)	(0.101)
Female	0.526	0.017	-0.003	0.500	0.025	0.004
	[0.499]	(0.308)	(0.887)	[0.500]	(0.294)	(0.922)
Minority	0.384	-0.131	-0.161	0.452	-0.208	-0.172
	[0.486]	(0.212)	(0.186)	[0.498]	(0.045)	(0.119)
Age	0.842	0.029	-0.012	0.819	-0.020	-0.062
	[0.365]	(0.323)	(0.711)	[0.385]	(0.718)	(0.276)
STEM	0.697	-0.015	0.021	0.811	-0.053	-0.002
	[0.459]	(0.684)	(0.631)	[0.392]	(0.163)	(0.969)
Repeater	0.146	0.034	-0.028	0.139	-0.011	-0.133
	[0.353]	(0.368)	(0.623)	[0.346]	(0.874)	(0.289)
CEE score	0.364	-0.120	0.141	1.237	0.082	0.159
	[0.852]	(0.571)	(0.581)	[0.402]	(0.390)	(0.205)
B. School-level results (unweighted) using student data in 2016						
Rural	0.556	0.121	0.002	0.650	0.113	-0.013
	[0.311]	(0.257)	(0.990)	[0.305]	(0.352)	(0.930)
Female	0.526	0.015	0.032*	0.500	0.037	-0.002
	[0.034]	(0.454)	(0.062)	[0.036]	(0.204)	(0.925)
Minority	0.384	-0.044	-0.083	0.452	-0.038	-0.040
	[0.159]	(0.602)	(0.422)	[0.173]	(0.673)	(0.759)
Age	0.842	0.039	0.000	0.819	0.021	-0.042
	[0.053]	(0.125)	(0.994)	[0.062]	(0.647)	(0.431)
STEM	0.697	-0.002	0.033	0.811	-0.525	0.008
	[0.082]	(0.960)	(0.554)	[0.057]	(0.278)	(0.874)
Repeater	0.146	0.016	-0.022	0.139	0.043	-0.130
	[0.056]	(0.616)	(0.542)	[0.134]	(0.668)	(0.271)
CEE score	0.364	-0.087	0.173	1.237	0.021	0.078
	[0.408]	(0.681)	(0.507)	[0.099]	(0.696)	(0.200)
C. School data in 2013						
Students	3,016.1	-340.8	332.6			
	[1,953.2]	(0.653)	(0.662)			
Full-time teachers	204.5	-6.3	64.1			
	[144.2]	(0.891)	(0.186)			
Part-time teachers	11.3	-3.9	-7.9			
	[15.7]	(0.548)	(0.245)			
Buildings	13.9	-2.9	-3.7			
	[7.7]	(0.461)	(0.370)			
Assets (in 1000)	24.6	-1.8	-5.0			
	[21.1]	(0.774)	(0.582)			
Books	5.2	2.9	5.6			
	[7.9]	(0.633)	(0.247)			
Total revenue	12,170.8	632.0	1,668.7			
	[3,754.7]	(0.740)	(0.356)			
Fiscal revenue	8,578.6	-304.5	546.7			
	[2,318.8]	(0.798)	(0.688)			
Tuitions	1,143.7	-326.3	-545.0			
	[756.8]	(0.371)	(0.159)			
Total spending	12,686.5	711.5	2,237.1			
	[3,868.8]	(0.682)	(0.289)			
Salary spending	2,035.9	-334.6	-61.0			
	[895.5]	(0.206)	(0.788)			
Operation spending	2,205.0	244.1	276.7			
	[1,103.9]	(0.574)	(0.561)			

Notes: This table reports the balance checks results using student/school-level observations of student data in 2016, and school finance data in 2013. The latter was used for randomization and initial balance checks. Random inference (and its p-value, reported in parentheses) is from 1,000 times permutations. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.8: Balance checks: Prediction of treatment status using student-level covariates in 2016 RCT

	All students		High achieving students	
	T1	T2	T1	T2
	(1)	(2)	(3)	(4)
Rural	-0.007	-0.019	-0.130	-0.007
	(0.077)	(0.059)	(0.130)	(0.041)
Female	0.010	0.001	0.004	0.006
	(0.007)	(0.011)	(0.011)	(0.010)
Minority	-0.112*	-0.106	-0.122*	-0.057
	(0.060)	(0.073)	(0.062)	(0.044)
Age	0.030	0.028	0.020	0.023
	(0.019)	(0.018)	(0.018)	(0.014)
STEM	-0.009	0.025	-0.021	0.057
	(0.023)	(0.039)	(0.043)	(0.043)
Repeater	0.027	-0.033	-0.027	-0.052
	(0.037)	(0.023)	(0.032)	(0.062)
CEE score	-0.015	0.023	0.057	0.069
	(0.027)	(0.045)	(0.038)	(0.042)
2.STRATA	0.366	0.546**	0.200	0.407
	(0.232)	(0.238)	(0.269)	(0.253)
3.STRATA	0.658***	0.709***	0.692***	0.885***
	(0.223)	(0.227)	(0.214)	(0.113)
4.STRATA	0.667***	0.696**	0.707***	0.771***
	(0.206)	(0.254)	(0.186)	(0.218)
Constant	0.130	0.002	0.185	-0.117
	(0.138)	(0.027)	(0.235)	(0.075)
F test	1.215	1.946	0.745	1.094
(P value)	0.335	0.121	0.637	0.407
Observations	24,231	20,011	5,831	5,738
R-squared	0.395	0.426	0.478	0.680

Notes: This table reports the balance checks results from separate OLS regressions that predict the treatment status using student-level data in 2016. Each column is from a separate regression. Strata fixed effects are included. Joint F test results are reported at the bottom of the table. Standard errors in parentheses are clustered at high schools. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.9: ITT effects on additional college access and match outcomes

	Application (=1) (1)	Enrollment in 2016 (=1) (2)	Repeating in 2017 (=1) (3)	Match (=1) (4)	Overmatch (=1) (5)
Control mean	0.914	0.777	0.206	0.608	0.096
Control s.d.	[0.280]	[0.416]	[0.405]	[0.488]	[0.294]
T1 (guidebook)	0.012	0.022	-0.028	0.035*	0.005
	(0.467)	(0.358)	(0.287)	(0.055)	(0.619)
T2 (workshop)	0.012	0.030	-0.052	0.016	0.010
	(0.573)	(0.304)	(0.104)	(0.447)	(0.398)
N	32,834	32,834	32,834	32,834	32,834

Notes: This table reports the OLS regression (Equation 2) results of the ITT effects of the guidebook and workshop interventions in 2016 on additional college access and match outcomes. **Enrollment in 2016** denotes students who received college admissions and did not repeat in 2017 (we do not have data from colleges about their actual enrollment status). **Repeating in 2017** denotes students who took CEE in 2016 and in 2017. **Match** indicates that a student's admitted college median score is within 0.25 s.d. radius of her own CEE score. All regressions control for student-level covariates (CEE score and demographics) and strata fixed effects. Randomization inference p-values from 1,000 permutations are in parentheses (clustered at high school level). * significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.10: ITT effects on college choice behaviors for high achieving students: Principal-component factors

	Index	Strategy			Preference		
		General	Targeting	Special programs	Tuition & quota	Location	Major
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Control mean	0.701	0.174	0.572	0.803	-0.009	0.677	-0.061
Control sd	[0.878]	[0.887]	[0.881]	[1.030]	[0.684]	[1.009]	[1.065]
T1 (guidebook)	0.093	0.084	0.074	-0.051	-0.118	0.144	0.044
	(0.273)	(0.358)	(0.137)	(0.653)	(0.140)	(0.140)	(0.293)
T2 (workshop)	0.229**	0.091	0.134**	-0.003	-0.219**	0.309***	0.074
	(0.016)	(0.326)	(0.034)	(0.969)	(0.014)	(0.010)	(0.164)
N	7,973	7,973	7,973	7,973	7,973	7,973	7,973

Notes: This table reports the OLS regression (Equation 2) results of the ITT effects of the guidebook and workshop interventions in 2016 on college choice behaviors. Strategies and preferences are constructed using college application data, as described in Appendix Subsection C.1. Sample includes high-achieving students in the randomization sample and submitted their college applications. We use principal component factor analysis to create a single index for each strategy and preference group, and an index for all (in column 1). All regressions control for student-level covariates (CEE score and demographics) and strata fixed effects. Randomization inference p-values from 1,000 permutations are in parentheses (clustered at high school level). * significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.11: ITT effects on college access and match outcomes for high achieving students

A. Main outcomes

	Admission (=1) (1)	Index (s.d.) (2)	Index* (s.d.) (3)	Undermatch (=1) (4)
Control mean	0.998	1.122	1.075	0.192
Control s.d.	[0.044]	[0.361]	[0.428]	[0.394]
T1 (guidebook)	0.001	0.058**	0.066**	-0.038
	(0.513)	(0.030)	(0.036)	(0.178)
T2 (workshop)	0.001	0.080***	0.092***	-0.066**
	(0.078)	(0.010)	(0.007)	(0.028)
N	7,977	7,977	7,961	7,977

B. Outcomes in Index (in column 2)

	College median (s.d.) (5)	College mean (s.d.) (6)	College min (s.d.) (7)	Quality (s.d.) (8)	Ranking (pctl) (9)
Control mean	1.130	1.130	0.285	1.447	89.902
Control s.d.	[0.449]	[0.436]	[1.202]	[0.490]	[7.184]
T1 (guidebook)	0.041*	0.042*	0.216***	0.050**	0.804**
	(0.067)	(0.058)	(0.005)	(0.041)	(0.038)
T2 (workshop)	0.056**	0.054**	0.298**	0.065**	1.215**
	(0.026)	(0..026)	(0.012)	(0.021)	(0.018)

C. Other outcomes

	Application (=1) (10)	Enrollment in 2016 (=1) (11)	Repeating in 2017 (=1) (12)	Match (=1) (13)	Overmatch (=1) (14)
Control mean	1.000	0.978	0.022	0.768	0.040
Control s.d.	[0.017]	[0.148]	[0.148]	[0.422]	[0.196]
T1 (guidebook)	-0.000	0.011*	-0.011*	0.027	0.012
	(0.937)	(0.053)	(0.056)	(0.303)	(0.160)
T2 (workshop)	-0.001	0.003	-0.003	0.057*	0.009
	(0.677)	(0.653)	(0.639)	(0.056)	(0.317)

Notes: This table reports the OLS regression (Equation 2) results of the ITT effects of the guidebook and workshop interventions in 2016 on a family of college access and match outcomes for high-achieving students. High-achieving students include those who were eligible for admissions at selective (tier 1) colleges. Outcomes are the same as described previously. All regressions control for student-level covariates (CEE score and demographics) and strata fixed effects. Randomization inference p-values from 1,000 permutations are in parentheses (clustered at high school level). * significant at 10%, ** significant at 5%, *** significant at 1%.

Table B.12: Effects of the individualized advising program

	Sample: High achieving students				
	Admissions	Index	College median	College quality	College ranking
	(1)	(2)	(3)	(4)	(5)
		A. ITT effects (excluding workshop & voucher schools)			
T2 (workshop)	-0.002	0.077***	0.039*	0.041	0.993**
	(0.002)	(0.021)	(0.021)	(0.029)	(0.383)
T1 (guidebook)	0.001	0.059***	0.040**	0.046**	0.741**
	(0.001)	(0.019)	(0.019)	(0.022)	(0.301)
		B. ITT effects (excluding workshop & no-voucher schools)			
T2 (workshop)	0.002	0.081***	0.059***	0.069***	1.286***
	(0.002)	(0.022)	(0.017)	(0.019)	(0.329)
T1 (guidebook)	0.001	0.057***	0.040**	0.049**	0.795**
	(0.001)	(0.020)	(0.019)	(0.021)	(0.289)

Notes: This table shows the estimates separately by voucher (for one-on-one advising) and no-voucher schools. See the text for more information. All regressions control for student covariates and strata fixed effects. Standard errors in parentheses are clustered at high school level. * significant at 10%, ** significant at 5%, *** significant at 1%.

C. Additional descriptions

C.1. Measuring college application behaviors and their correlations with college admissions

C.1.1 Tier-specific college applications in Chinese centralized admissions

As introduced in Subsection 2.2, college applications and admissions in China proceed by institutional selectivity tiers within province-track. Each college-major belongs to a predetermined tier (a college may have majors in different tiers). A student's eligibility to apply to colleges in each tier is mostly determined by her CEE score. She could apply to Tier 1 if and only if her CEE score is above the tier-specific cutoff score. She can also apply to the other tiers. A student could only apply to Tier 4 colleges if her CEE score is below Tier 3 cutoff. Few students could not apply to any college with CEE score below the very low Tier 4 cutoff (200 raw points out of 750).

Table C.1 shows a simplified version of the college application form in Ningxia in 2016. On the one hand, the application (administrative) process is simplified. Many common requirements in decentralized admissions systems (e.g., score-sending, institution-specific essays, AP courses, reference letters) are no longer needed. Students need to choose colleges and majors of their interests from the pull-down menu in the online application system. If they already have a list of interested and majors at hand, they can finish the application process in minutes.

On the other hand, the application is complicated. Students would have to consider every cell in the application form in Table C.1. They need to build knowledge and skills to pick colleges and majors strategically. Therefore, a knowledge-based intervention on the use of college choice knowledge and skills would improve students' applications and admissions.

The application form corresponds to the order of admissions. Within each institutional tier, there are several special programs that could be seen as sub-tiers within each tier. For instance, in addition to the primary Tier 1 (choice of four colleges), students who are eligible for Tier 1 admissions could potentially apply to (1) Tier 1 - Early Admissions, (2) Tier 1 - National Affirmative Action Programs for Rural Poor Students, (3) Tier 1 - Provincial Affirmative Action Programs for

Rural Poor Students, (4) Tier 1 - Affirmative Action Programs for Minority Students, and (5) Tier 1 - Other Special Programs (e.g., College-level Affirmative Action Programs for Rural Poor Students). In Ningxia in 2016, a student, in theory, could apply to 58 different colleges (out of about 1,200 colleges) and then 348 college-major options (out of about 20,000).[42]

[42]There are 2,631 colleges in China (not including military colleges; till May 2017). But not all of them admit students from Ningxia.

Table C.1: College application form in Ningxia in 2016 (Simplified)

ID: Name: Track:

Tier	No.	College	Major						Flexible
			1	2	3	4	5	6	assignment?
Tier 1 - Early admissions	1								
	2								
Tier 2 - EA	1								
	1								
Tier 1 - National Affirmative Action (Rural)	A								
	B								
	C								
Tier 1	A								
	B								
	C								
	D								
Tier 1 - Provincial AA (Rural)	A								
	B								
Tier 1 - AA (Minority)	A								
	B								
	C								
Tier 1 - Special majors	1								
Tier 2	A								
	B								
	C								
	D								
Tier 2 - AA (Minority)	A								
	B								
	C								
Tier 2 - Special majors	1								
Tier 3	A								
	B								
	C								
	D								
Tier 3 - AA (Minority)	A								
	B								
	C								
Tier 4 - EA	1								
Tier 4	A								
	B								
	C								
	D								

Notes: This table adopts the original Chinese version of the application form and excludes a few rows of special program lists. In Ningxia in 2016, a student, in theory, could apply to 58 different colleges and then 348 college-major options. Data source: Baidu Wenku. Numbers in the "No." column indicates the admissions are based on the Boston Mechanism, and letters in that column indicates the admissions are based on the DA (Parallel) Mechanism.

C.1.2 Measuring college application behaviors using actual choice data

Based on features of the tier-specific applications in the Chinese centralized college admission system, we focus on three sets of strategies. These strategies are expected to capture some of the main application behaviors for a knowledgeable and skillful student. We have also covered these strategies in our interventions from the application guide "textbook", to school workshop, and to personalized advising. The first set variables describe some general guidelines (or simple information/strategy):

- **[Strategy 1.1] Number of applied colleges.** <u>The behavioral rationale</u> is that increased applications are positively correlated with increased college opportunities (e.g., Pallais, 2015; Hurwitz et al., 2017). However, applying to too many colleges without caution may result in undermatched colleges in some early admissions or special programs. A common mistake that we have observed in the field and from the data is that many Tier 1 eligible students incorrectly applied to colleges in "Tier 2 - Early Admissions." Colleges in "Tier 2 - Early Admissions admit students before those in "Tier 1" that these students missed their chances of much higher quality colleges in Tier 1. <u>We construct this variable</u> by counting the total number of all the colleges that a student applied to. <u>Sample mean</u> (using the untreated sample in 2016, see descriptions in the main text) is 7.2, with a minimum of 1 and a maximum of 40. <u>The strategy</u> is not deterministic that we recommend students to think about their applications carefully and the number of colleges to apply to is related to the targeting strategies in the second set variables.
- **[Strategy 1.2] Percent of applied majors.** <u>The behavioral rationale</u> is that, unless students are strongly against specific majors and they could bear the risks of being rejected by a college that considers her admission, students should fill in all the six major options within each college (or the maximum number of majors in that college). This is because that the college-then-major admissions give each student only one college temporary admission chance. If a student is eventually rejected by a college due to the unmatched of major applications, she

will not be considered by other colleges in the same institutional tier and has to move down to lower tiers. In practice, many students only have strong major preferences, but do not understand the need for this strategy to reduce their rejection risks. We construct this variable by calculating the percent of major applications over total available major numbers given the colleges that a student applied to. Sample mean is 69.9%, with a minimum of 16.7% and a maximum of 100%.

- **[Strategy 1.3] Percent of flexible major assignment.** The behavioral rationale is that flexible major assignment minimizes the risks of being rejected by a college due to unmet major choices, which happens when all the majors within a college that a student applies to have higher admissions scores than her CEE score. If that student accepts flexible major assignment within that college, then the college will assign her to a major that still has a spot (but that major may not be her interested one). The flexible assignment is actually to increase admission probability by sacrificing major preferences. We construct this variable by calculating the percent of college applications accepting flexible major assignment over the number of applied colleges. Sample mean is 69.2% with a minimum of 0 and a maximum of 100%. The strategy, which we strong nudged every student to use, is to accept a flexible major assignment at most of the applied colleges, if not all of them.

The second set of variables describe the targeting strategies that students should use to apply to a combination of peer, reach/match and safety colleges (and majors). This strategy requires the most intensive knowledge and sophistication to make the accurate predictions and decisions. This set of strategies are the key elements of our behavioral interventions as well as the data analysis in a students' college choice and application. Many students do not understand the underlying mechanisms of college admissions that only rank (but not raw score) matters. They naively compare their CEE score in this year with college admissions raw scores, which results in large errors of identifying college types. Students may use different strategies in different tiers, but we use their behaviors in their match tier to represent their general knowledge and skills in college applications. A match tier is the highest possible institutional selectivity tier that a student qualifies for, which is similar to the use of selectivity tiers in defining undermatch in the literature (e.g., Smith, Pender and Howell, 2013). Besides, we focus on college-level application behaviors, but those choices of majors within each college is also worth exploring in the future research.

- **[Strategy 2.1] Estimated gap (within 0.15 s.d.).** The behavioral rationale is that students should equate their CEE score to admissions scores in the previous years. For example, suppose that the raw CEE scores are 500 and 550 for a student ranked 10,000 in 2016 and 2015, a student in 2016 with CEE score of 500 should then look at colleges with admissions scores around 550 in 2015. If she applied to colleges with admissions scores around 500 in 2015, she would be very much likely to undermatch. The raw scores vary dramatically over the years. Suppose that the raw CEE scores are 600 and 550 for a student ranked 10,000 in 2016 and 2015, if a student with CEE score of 600 in 2016 applied to colleges with admissions scores around 600 in 2015, she would not be likely to be admitted by an undermatched college, but being rejected by all of her applied colleges. We construct this variable by estimating the gap (difference) between one's CEE score in 2016 and the equated median score (from 2015 to 2016) of the college she listed in the second college choice in the match tier.[43] This variable equals to 1 if the estimated gap is within 0.15 s.d.. Sample mean is 34%. The strategy is that students need to acquire the knowledge of score equating (and the principle of why score equating is needed) as well as data of the crosswalks between raw scores and rankings over the years. They need to do the score equating by themselves before choosing colleges and majors to apply for.[44]
- **[Strategy 2.2] Apply to colleges in the match tier.** The behavioral rationale is that students would have access to most of their peer/match colleges in the match tier. Students may have behavioral mistakes of not applying to the match tier but only to colleges in lower tiers, or they only applied to special programs but not to colleges in the primary sub-tier.

[43] We choose the second choice order as that it is expected that a student should apply to a match college in here second or third choice (first choice as a reach college and last choice as a safety choice). Results are very stable if we use other choices or a summary statistic of these choices.

[44] Figure A.3 shows that, though correctly centered, a large proportion of students apply to colleges that they would be substantially undermtached or overmatched. It is very likely because they do not (understand and) do score equating. From our fieldwork observations, high school teachers also lack the knowledge about score equating.

We construct this variable by identifying students who did not apply to colleges in match tier. Sample mean is 23% that about 23 percent of students in 2016 (in the untreated sample) did not apply to colleges in match tier. This number does not include those who did not submit their college applications.[45]

- **[Strategy 2.3] Apply to colleges without admissions data in the prior year.** The number of colleges that admit students in one province may change over time. Each year there are "new" colleges for students to apply to. The behavioral rationale is that students need to infer/predict the admissions data in previous years for these "new" colleges using other information, and they may take risks of applying to these colleges. However, if most students are risk-averse and do not apply to those colleges, it is a good opportunity for skillful students to gain an overmatched admission. We construct this variable by identifying students who applied to colleges in the match tier without admissions data in the prior year. Sample mean is 2%.
- **[Strategy 2.4] Descending order of colleges in the match tier.** The behavioral rationale is that students should apply to a mix of reach, peer and safety colleges to maximize their opportunities of getting into reach and peer colleges, and to minimize the risks of being rejected by all (Hoxby and Avery, 2013). In order to correctly identify types of reach, peer and safety colleges, students need to understand the classification of these types (a rule of thumb is a 0.05-0.15 s.d. threshold) based on score-equating. Then, for the four college choices within each tier, given the institutional feature of Differed Acceptance (Parallel) mechanism, students should list their four choices in the descending order (choice A > choice B > choice C > choice D), otherwise any choices in higher orders with higher *ex post* admissions scores are meaningless. We construct this variable by a dichotomous indicator of students who did so in their match tier. Sample mean is 31%.
- **[Strategy 2.5] Targeting.** The behavioral rationale is that, although students are nudged to

[45] For students who prefer low tuitions and are only eligible for Tier 3 and 4 colleges, one rational choice is that they may not be interested in colleges in Tier 3 (private four-year colleges with high tuitions) and only applied to Tier 4 colleges.

apply to a mix of reach, peer and safety colleges, they should not aim too high or too low. In other words, they need to have a tight range of colleges (centering around their CEE scores). We construct this variable by a dichotomous indicator of students with differences in college median score in the prior year between the first college choice and the last choice in the match tier in the range of (0, 0.5 s.d.). Sample mean 35%.

The third set of strategies regard special programs that students may lack awareness and information and knowledge to understand these policies. One example is that the affirmative action programs for minority students vary greatly in college quality between national programs and in-province programs. Students may apply for both and end up with lower quality in-province colleges.

- **[Strategy 3.1] Minority affirmative action programs.** The behavioral rationale is that students may lack information and knowledge to differentiate/understand different AA programs. National AA programs are of high quality (in selective colleges), but provincial AA programs are lower-quality. We construct this variable by identifying that if a student applied to any AA programs. Sample mean is 22%, with a minimum of 0 and a maximum of 1.
- **[Strategy 3.2] Early admissions.** The behavioral rationale is that students may lack awareness of these programs and understanding of the policy. For example, the rural poor student affirmative action programs at selective colleges need pre-registry several months before CEE, but many students did not complete the registration. We construct this variable by identifying that if a student applied to any early admissions programs. Sample mean is 15%, with a minimum of 0 and a maximum of 1.
- **[Strategy 3.3] Teachers' education.** The behavioral rationale is that these special teachers' education programs may be opportunities to enter higher quality colleges (based on one's CEE score). However, students may have strong major preferences. We construct this variable by counting the percent of applied majors in teacher's education. Sample mean is 5.2%, with a minimum of 1 and a maximum of 40.

Student preferences and tastes are individual-specific strictly unobservable. Particularly in constrained college applications, revealed preferences may not be precisely true. We construct three sets of proxy preferences using the application data. The first set includes college tuition and quota, which are the primary information provided to students by the Department of Education.

- **[Preference 1] College tuition and quota.** The behavioral rationale is that low-income students may prefer low-tuition colleges, and risk-averse students may prefer college with larger admissions quota (Dynarski and Scott-Clayton, 2013; Hoxby and Avery, 2013; Loyalka, Wu and Ye, 2017). In China, selective colleges have lower tuitions than non-selective colleges. Within selectivity, tuitions vary across locations, college types and majors. Students may also use tuition as a naive indicator of college quality. College quota may be positively correlated with admissions probability (Kamada and Kojima, 2015), but students may be unaware of the quota information, which is provided to them by the Department of Education. We construct these variables by using median college tuition of all applied colleges and mean quota of all applied colleges. Sample mean of tuition is 6,300, with a minimum of 0 and a maximum of 40,700. Sample mean of quota is 708, with a minimum of 1 and a maximum of 2,993.

The second set of preference variables are the college location choices:

- **[Preference 2.1] Out-of-province colleges.** The behavioral rationale is that distance is one important factor shaping students' college choices but focusing on in-province colleges would limit other high-quality college opportunities. It is also true in Ningxia that high-quality colleges concentrate in the economically developed regions in China. Ningxia province, as a low-income region, lacks high-quality colleges. We construct this variable by calculating the percent of applied colleges locating in out-of-province regions (excluding economically advanced regions and Ningxia's neighborhood provinces). Sample mean is 38.8%, with a minimum of 0 and a maximum of 1.

- **[Preference 2.2] Out-of-province (advanced regions) colleges.** We construct this variable by calculating the percent of applied colleges locating in the most economically advanced regions of China, including Beijing, Shanghai, Guangdong. Sample mean is 6.6%, with a minimum of 0 and a maximum of 1.

The last set of preferences are major choices. We include the most popular ones (e.g., economics, computer science, international) and the least popular agricultural-related majors in the analytical variables.

- **[Preference 3] Majors.** We construct these variables by calculating the percent of each major group over the total number of applied majors. The mean values of Economics-related, Agricultural-related, Computer science-related, International-related, and Medical-related are 24.1%, 1.3%, 3.2%, 1.6%, 11.4%. We did not provide direct interventions on major choice but provided information about all the majors (e.g., coursework, college life, labor market outcomes). We nudged students to get to know each major well before making decisions. Additionally, this is also related to application strategies (e.g., flexible major assignment, targeting).

C.1.3 Correlations between applications and admissions

In Table 2, we extend Equation 1 by including the measures of our constructed strategies and preferences to examine how much they could explain the rural-urban gap in college match. Column (1) estimates the same full model controlling for CEE score and demographics as in column (2) of Table B.3; column (2) excludes students who do not apply to college. The rural-urban gap decreases from -0.176 s.d. to -0.123 s.d., but remains statistically significant. Column (3) controls for high school fixed effects, which could capture the differential access to information and guidance between schools. The gap substantially decreases; however, it remains both economically and statistically significant.

In columns (4)-(7), we add each set of strategies and preferences (principal component factor index) stepwise. Assuming that rural students follow the same general advice with urban students, column (4) show that the gap decreases by 0.05 s.d.. Holding targeting strategies equal, the rural-urban gap largely decreases by 0.34 s.d., about half of the gap in column (4). Coefficients on the targeting strategies measures show that applying appropriately for peer, reach and safety colleges significantly improves college match. Special programs and college-major preferences do not explain much of the gap, while a few of the individual items are significantly correlated with college median score (Table C.2), but between rural and urban group differences may be smaller than within-group individual heterogeneities. In Table C.2, we report regression results using the itemized measures. The first two columns show the sample average in each measure between rural students and urban students. Consistently, among all the strategy and preference measures, targeting strategies explain the largest proportion of variations in college match.

Alternatively, Oaxaca-Blinder decomposition shows a very consistent story. About 0.065 s.d. of the 0.105 s.d. estimated rural-urban gap (rural: 0.082; urban: 0.187) in college median score, controlling for CEE score and demographics, is explained by rural-urban differences in the college choice strategies and preferences that we construct. The set of targeting strategies explain a 0.070 s.d. in the rural-urban gap.

We also use Oaxaca-Blinder decomposition to examine the between-group differences in applications and admissions. About 0.078 s.d. of the 0.132s.d. estimated rural-urban gap (rural: 0.058; urban: 0.189) in college match index, controlling for CEE score and demographics, is explained by rural-urban differences in the college choice strategies and preferences that we construct. The set of targeting strategies explain a 0.065 s.d. (83% of the explained differences) in the rural-urban gap. The other strategies and preferences explain very small differences (general advice: 0.008 s.d.; special program: -0.001 s.d.; location: -0.009 s.d.; tuition & quota: 0.013 s.d.; majors: 0.003 s.d.).

Table C.2: College choices and the rural-urban gap in admissions outcomes

		Sample mean		Outcome: Index of college match				
		Rural	Urban					
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rural-urban gap				-0.074***	-0.067***	-0.026***	-0.028***	-0.029***
				(0.012)	(0.012)	(0.007)	(0.007)	(0.007)
# of colleges applied	Strategy 1	7.4	6.9		0.034***	0.019***	0.022***	0.022***
					(0.003)	(0.003)	(0.004)	(0.004)
# of colleges applied2̂	Strategy 1				-0.001***	-0.001***	-0.001***	-0.001***
					(0.000)	(0.000)	(0.000)	(0.000)
% of majors applied	Strategy 1	67.3	73.1		0.001***	0.000	0.000*	0.000*
					(0.000)	(0.000)	(0.000)	(0.000)
% flexible major assignment	Strategy 1	63.4	76.4		0.000***	0.000***	0.000***	0.000***
					(0.000)	(0.000)	(0.000)	(0.000)
Estimated gap within 0.15 s.d. (=1)	Strategy 2	0.33	0.43			0.043***	0.046***	0.054***
						(0.008)	(0.008)	(0.008)
Did not apply for matched tier (=1)	Strategy 2	0.19	0.10			-0.526***	-0.515***	-0.518***
						(0.032)	(0.033)	(0.032)
Missing prior year data (=1)	Strategy 2	0.01	0.03			0.049***	0.049***	0.032**
						(0.012)	(0.012)	(0.012)
Descending (=1)	Strategy 2	0.27	0.41			0.097***	0.095***	0.082***
						(0.006)	(0.005)	(0.005)
Targeting (=1)	Strategy 2	0.32	0.45			0.035***	0.033***	0.031***
						(0.006)	(0.006)	(0.005)
Affirmative action (=1)	Strategy 3	0.29	0.19				-0.073***	-0.048***
							(0.013)	(0.012)
Early admissions (=1)	Strategy 3	0.16	0.17				0.046***	0.016*
							(0.010)	(0.009)
% teachers' colleges	Strategy 3	6.3	3.8				0.002***	0.002***
							(0.000)	(0.001)
College tuition (1000 RMB)	Preference 1	5812	6838					-0.024***
								(0.002)
College quota	Preference 1	860	518					-0.000*
								(0.000)
% out of province	Preference 2	29.3	50.6					0.001***
								(0.000)
% advanced regions	Preference 2	4.5	9.1					0.002***
								(0.000)
% economics majors	Preference 3	22.6	26.0					0.002***
								(0.000)
% agricultural majors	Preference 3	1.3	1.3					0.000
								(0.001)
% CS majors	Preference 3	2.9	3.5					0.004***
								(0.000)
% international majors	Preference 3	1.2	2.1					-0.002*
								(0.001)
% medical majors	Preference 3	12.8	9.7					0.001***
								(0.000)
Observations				28,806	28,806	28,806	28,806	28,806
R-squared				0.665	0.669	0.724	0.726	0.733

Notes: This table reports the OLS regression (Equation 1) results of the correlations between college application behaviors and college match index, using data from those who submitted college applications in the untreated sample in 2016. Columns (1) and (2) report sample mean for rural and urban students. Regressions in columns (3)-(7) include a student's CEE score and other demographic covariates, as well as high school fixed effects. Standard errors in parentheses are clustered at high school level. * significant at 10%, ** significant at 5%, *** significant at 1%.

C.2. Intervention Descriptions (Guidebook & workshop)

C.2.1 The guidebook

The "How to Apply to College?" guidebook is to prepare all the relevant information and strategies that a student should have in the process of college choice and application. In 2016, we distributed the printed guidebook to treated students through high schools (on June 20). In 2017, we no longer distributed the printed version, but used the electronic version for students in the "machine learning" advising group.

On the cover of the guidebook (Panels A and C in Figure C.1), we label that the guidebook is provided by a research team at Peking University (in 2016, as a joint team of Peking University and Ningxia University, the latter is the best college in Ningxia).

The outline of the guidebook is as follows (Panel D of Figure C.1):

1. Six steps in college applications
   (a) Score equating
   (b) Make use of past admissions data
   (c) Select a short list of colleges
   (d) Identify the reach, peer and safety colleges and apply to a mix set of them
   (e) Major choices within each college
   (f) Tier-specific plans (with a focus on the match tier)
2. Understanding college admissions policies
   (a) Background: Track, Tiers, Tier cutoff
   (b) Deferred Acceptance (Parallel) mechanism
   (c) College-then-major admissions
      - Major admissions rules
      - Flexible assignment
      - Rejection and re-application
3. Supplemental materials
   (a) Understanding the strategies of targeting reach, peer and safety college
   (b) Useful information
      - Make use of your "advantages" (based on preference differentials)
      - Information and data collection
      - Recommended online sources (Panel A of Figure C.2)
      - National employment trends by majors (Panel B of Figure C.2)
   (c) Application guidelines and tips

Recommended online sources. In preparing the guidebook, besides summarizing our own experience and knowledge, we have learned greatly from existing sources. Our research team carefully reviewed more than 200 Chinese websites and guidebooks that contained information about college entrance exam and college applications. We have also learned greatly from some excellent resources in the U.S., such as MDRC's "In Search of a Match: A Guide for Helping Students Make Informed College Choices" and the College Board's Big Future program.

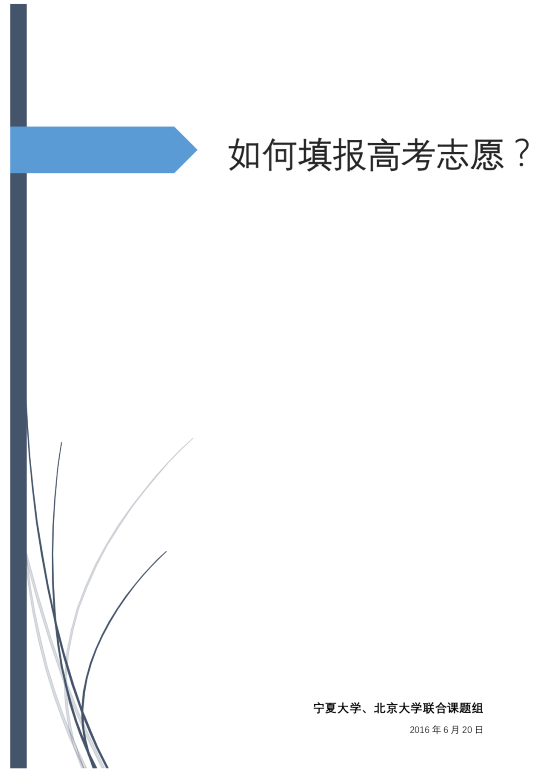
In the guidebook, we provide a summary some of the most reliable and useful information to guide students to find the resources for further information. As shown in Panel A of Figure C.2, we list nine "college applications" websites, each of them covers some of the information that we think is relevant to college choices and applications. From the left to the right, these information items are:

- College introduction (1)
- Schools, majors within each college (2, 3)
- College admissions guidelines (4)
- Admissions scores (5)
  - The most reliable source is the printed book provided by the provincial Department of Education; we also purchased a few copies in 2016 and 2017 for the one-on-one advising
- Housing and dinning (6)
- Recommended short list of colleges (7)
- Employment data (salary, locations; 8, 9)
- Degrees, major descriptions, coursework (10, 11, 12)
- Employment data (major-level salary, trends, locations; 13, 14 ,15)
- Student evaluation (college, major; 16, 17)
- Major recommendation scores (18)

C.2.2 School workshop in 2016

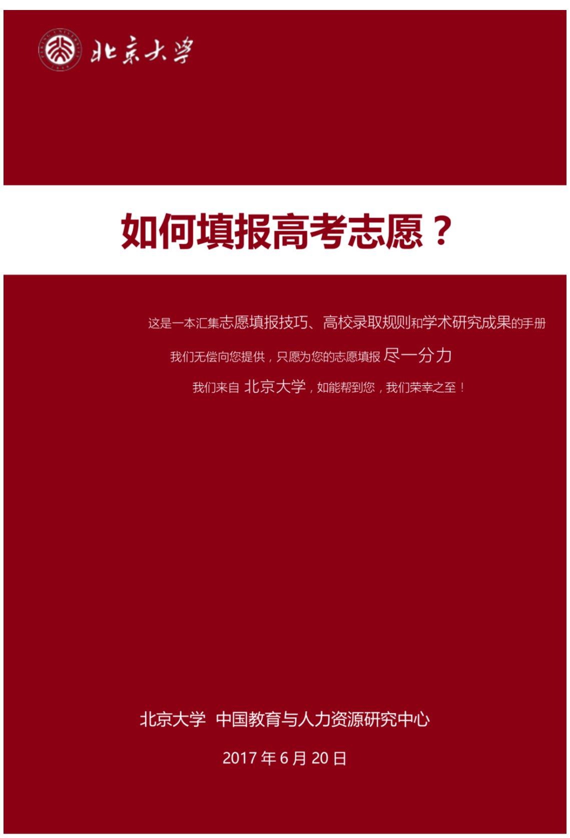
We provided school workshop in seven randomly chosen high schools. Workshops were organized by local district and high school schools. To minimize the quality variations in the workshops, we selected a group of very knowledgeable experts (editors of the guidebook) to give the workshop, using the same slides and scripts. Workshops were announced one month ahead of time in the name of a joint research team from Peking University (the top college in China) and Ningxia

University (the top college in Ningxia). Each workshop lasted for three hours and was moderated by a high-level school administrator. Figure C.3 and Figure C.4 show the sample pictures.

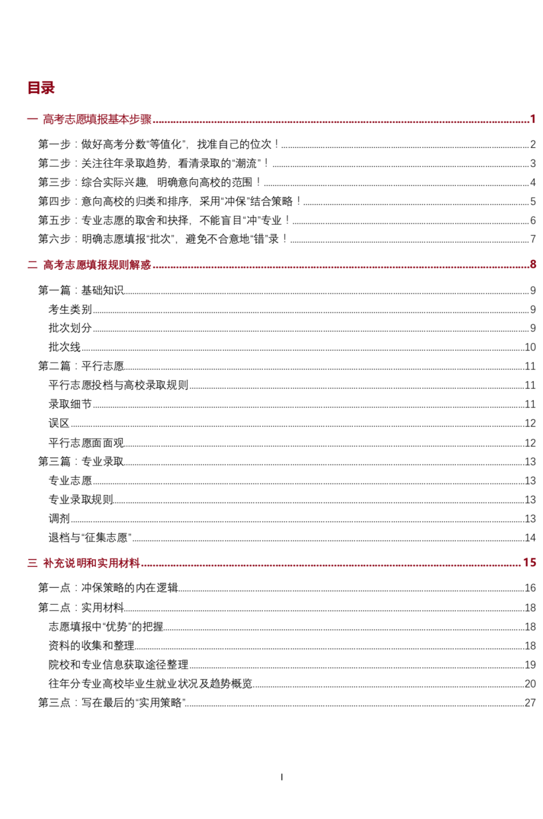


(a) Cover (2016 edition)

(b) Received packages from the press, 2016, Beijing



(c) Cover (2017 edition)



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I

(d) Outline (2017 edition)

Figure C.1: The guidebook "How to Apply to College?"

Notes: This figure shows sample pictures of the guidebook in 2016 and 2017.

表格 1 志愿信息参考网站一览

网站名称、网址	大学情况	院系设置	所设专业	招生章程	分数线	生活条件	估分推荐	学校就业起薪	学校就业去向	专业学位划分	专业培养目标	专业核心课程	专业就业起薪	专业就业趋势	就业方向	院校满意度	专业满意度	专业推荐度
新浪教育·高考院校库 http://kaoshi.edu.sina.com.cn/	√		√	√	√	√	√	√			√	√						
中国教育·在线高考志愿填报系统 http://gkcx.eol.cn/	√		√			√	√				√	√						
搜狐教育·搜狐大学信息库 http://daxue.learning.sohu.com/	√		√		√		√		√									
看准网·大学专业 http://www.kanzhun.com/dxjy/											√	√	√	√	√			
高考网·专业信息 http://college.gaokao.com/spelist/										√	√	√			√			
高三网·大学专业解读 http://www.gaosan.com/zhuanyejiedu/											√			√	√			
学信网·阳光高考 http://gaokao.chsi.com.cn/	√	√	√	√		√										√	√	√
第一高考网·找专业 http://www.diyigaokao.com/major/bklist.aspx											√		√		√			
中国教育在线 http://www.eol.cn/html/g/benkezy.shtml										√	√	√						

3

(a) Sumamry of reliable online resources

表格2 分专业本科毕业生规模结构与初次就业率

学科专业		2011年规模与结构		2011年初次就业率（%）	11-14年初次就业率变化趋势
学科门类	专业类	人数	百分比		
哲学	哲学类	2172	0	85	
经济学	经济学类	173853	6	88	
法学	法学类	74326	3	79	
	马克思主义理论类	193	0	90	
	社会学类	11424	0	85	
	政治学类	20058	1	84	
	公安学类	11288	0	77	
教育学	教育学类	36637	1	83	
	体育学类	55046	2	78	
	职业技术教育类	8621	0	91	

(b) Trends in employment rate by majors

Figure C.2: Sample contents in the guidebook “How to apply for college?”

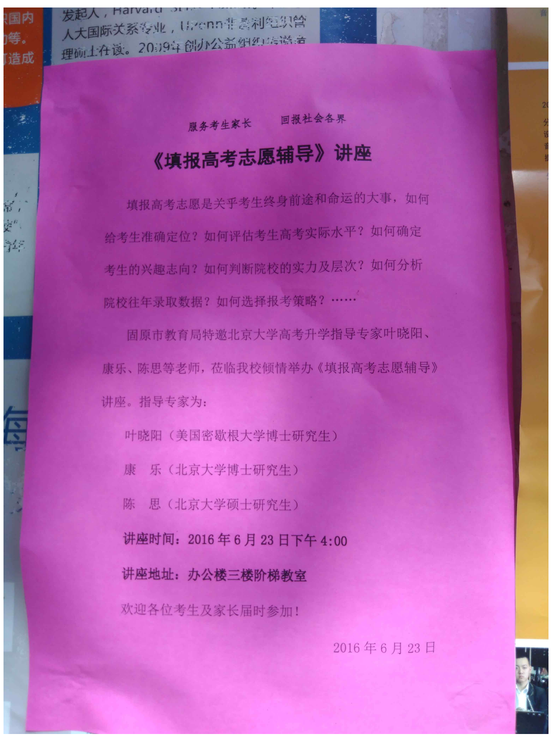
Notes: This figure shows sample contents in the guidebook. Panel A lists nine websites with a cross-tab of available information on each website that we selected from about 200 Chinese websites. Panel B shows that the employment trend graph by major that was created using data on every college graduate from 2011 to 2014.

(a) Guyuan No.1 High School (Speaker: Xiaoyang)

(b) Helan No.1 High School

Figure C.3: High school workshops in 2016

Notes: This figure shows sample pictures of the school workshops in 2016.



(a) School poster

(b) (Late) Q&A after workshop

Figure C.4: High school workshops in 2016 (Guyuan No.2 High School)

Notes: Figure A shows the school poster. The workshop was announced as organized by Guyuan City Department of Education. Figure B shows the brief conversations with students and parents after the three-hour workshop. The sentence on the back of the project tee "**Only the educated are free**" is from a Greek Stoic philosopher Epictetus (AD 55-135). While each workshop had one speaker, we had a team of 3-4 members there for brief follow-up Q&A after each workshop.