Improving Matching Equality in College Admissions:

Estimation and Policy Interventions in China

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Abstract

In this paper, we examine matching inequality in Chinese college admissions. We define matching inequality as the deviation from positive assortative matching (i.e., matching high-ability students with high-quality colleges). By estimating a model of student–college matching, we quantify the relative importance of two driving forces of matching inequality: students' heterogeneous preferences for colleges related to their socioeconomic status, and the regional distribution of college admissions quotas. The imperfect assortative matching is driven mainly by the uneven quota distributions. Among counterfactual policies, fully or partially consolidating provincial quotas into a national market would greatly improve the assortative matching without harming the disadvantaged students.

Keywords: college admissions, educational inequality, assortative matching

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I. Introduction

Education equality has been an important issue in college admission. The rate of return to college education remains high, and its impact on social mobility, including intergenerational as well as inter-regional mobility, has been well recognized. In many countries including China, the college admission rates are high and stable in recent years. The main policy focus has become the matching of colleges and students (Blanden, Doepke, and Stuhler, 2023; Levenheim and Smith, 2023).

Educational equality has been commonly defined as providing equal educational opportunities for people regardless of their socio-economic status (SES). However, this definition is not enough for college admissions, otherwise a purely random draw to go to college would achieve this goal. College applicants have put a lot of efforts for preparing college admissions and accumulating a large amount of pre-college human capital, which should be respected during college admissions. Therefore, a proper policy objective of college admissions would be two-folded: (1) to provide equal opportunities to students with equal pre-college human capital regardless of their SES, (2) to provide better (or larger) opportunities for students with higher pre-college human capital. From a theoretical point of view, a stable matching mechanism (e.g., deferred acceptance) in which colleges prioritize students purely on their pre-college human capital (or its proxy, such as college entrance exam scores or SATs) would achieve this goal. We call such an objective *matching equality,* and the target admissions as equal match (EM). The real-world college admissions mechanism, however, may deviate from achieving matching equality in three ways: (1) The matching outcome is unstable, due to its defective mechanism design. (2) College priorities are not purely based on student pre-college human capital. (3) Students may value college attributes other than college quality due to their SES.

In this paper, we examine whether the current Chinese college admissions system achieves educational equality. The system is broadly viewed as a well-functioned institution for achieving matching equality, because colleges admit students based purely on their exam scores in the nationwide unified examination (*gaokao*), arguably the best single measure of pre-college human capital (or student ability).[1] However, matching inequality may still exist. We find in this paper that, although college entrance exam scores have a large predictive power for the college quality students attend, those with higher socioeconomic status, namely, from higher-income, urban households and whose parents have better education, are still more likely to attend higher-quality colleges, given their *gaokao* scores. Furthermore, students differ greatly in their likelihood of attending elite colleges by where they come from. The probability of attending high-quality colleges of students from the least competitive province is five times more than that of students from the most competitive province (Figure A1 in Appendix).

We then explore two potential sources of the matching inequality in China's colleges admissions: college admission policies and student heterogeneous preferences.[2] We highlight two facts. First, the regional quota system in China may attribute to the large gap in higher education opportunities among different regions. Colleges allocate more quotas to home provinces and provinces with higher income. Given that high-quality colleges are disproportionally concentrated among richer regions, college preferences for local students and rich students can further reinforce each other and exacerbate the matching inequality.

Second, students may have preferences over college attributes other than college quality, induced by their SES. For example, students with different income may have different preferences for colleges' non-quality attributes, like tuition and distance from home. Strong preferences over these college attributes may overturn their largely homogeneous preferences over college quality and aggravate educational inequality.

We quantify the relative strength of these two influencing factors, i.e., regional quota distribution and student preference heterogeneity, by estimating a student–college matching model. Student preferences are based on different college attributes, including college quality, tuition, travel distance, and local economic conditions. The estimates show that students have a strong positive preference for college quality, and have a strong negative preference for the

[1] This paper assumes that the college entrance exam score is a noisy measure for student ability. We also do not distinguish student ability and pre-college human capital and use both terms interchangeably. More measures on student ability is discussed in Section 4.1.

[2] A large body of literature has focused on the first source of matching inequality in college admissions mentioned above, i.e., instability of matching outcomes due to mechanism design or student behaviors. See, for example, He (2015), Wu and Zhong (2020), Grenet, He, and Kübler (2022), Artemov, Che, and He (2023).

distance and net tuition of the college. Moreover, low-income students have much larger disutility from travel distance and net tuition than high-income students (more than double).

We then use the estimated student preferences to simulate the college admissions equilibrium outcomes in alternative scenarios. Specifically, we decompose the effect of student preference heterogeneity and quota distribution: first, we shut down the "preference-heterogeneity effect" by assuming all students have the same preference order over colleges based purely on college quality ranking. Second, we shut down the "quota distribution effects" by consolidating all students into a single national market, with the admissions based on cross-provincially comparable student abilities, for which we construct two measures: One is students' college entrance exam score percentiles *within* province and track; second is the pre-college human capital recovered from students' *gaokao* scores and college GPAs in a measurement model.

To compare various equilibrium matching outcomes, we use the positive assortative matching (i.e., PAM) as our benchmark and the deviation from it as the measure of matching inequality. PAM is defined as a matching outcome in which students with higher ability matching with colleges with higher quality. It can be regarded as a stable matching in which college priority is solely based on student ability and student preference is solely based on college quality. Assumedly, as we argued, the ideal benchmark would be equal match (EM), a stable matching in which college priorities are based solely on student ability and student preferences would not be affected by their SES (e.g., not be distorted by financial constraints), yet probably not solely determined by college quality. The problem is that such an "intrinsic" student preference unrelated to their SES is unobservable, and probably conceptually unidentifiable. We argue that PAM is the best alternative in our context without "measurement errors".

The argument can be illustrated in Figure 1. All the matchings outcomes are lined up according to their closeness to PAM. Equal match (EM) is the closest to PAM, because it rules out both biased college polices and student preferences induced by SES. The current matching observed in data is the furthest because it contains all distortions. The paper tries to find out whether match corrected for biased college polices (M1) or SES-induced student preference

(M2) to be closer to EM. Since both M1 and M2 must be further from PAM than EM, then getting closer to PAM is equivalent to getting closer to EM. The idea of using PAM to measure matching inequality (or mismatch) have recently been developed in literature (Dillon and Smith 2017, 2020; Wu and Zhong 2020). Our paper is among the first to use it for policy evaluation through counterfactual simulations based on a structural model.

We compare all counterfactual scenarios (i.e., M1 and M2, among others) as well as current match (CM) using two measures of deviation from positive assortative matching (PAM): the number of blocking pairs (Calsamiglia, Haeringer and Klijn 2010)[3] and the degree of mismatch (Wu and Zhong 2020).[4] As a result, we find that both heterogeneous preferences and provincial quota restrictions matter for imperfect assortative matching, while provincial quota restrictions matter more. By using the score percentile as the measure of student abilities, the average number of blocking pairs per student decrease by 75% from the current policy when removing provincial quotas, while decrease 56% by erasing heterogeneous preferences. By using the pre-college human capital, the average number of blocking pairs per student decrease by 90% when removing provincial quotas, while decease 21% by erasing heterogeneous preference. The results by using another measure of imperfect assortative matching, i.e., the degree of mismatch, are similar. Abandoning the provincial quota system therefore can greatly correct the imperfect assortative matching, and the corrective effects are not through harming the socioeconomically disadvantaged students. We also offer suggestive evidence that removing the provincial quota may also have positive impacts on student welfare. As a comparison, policies such as doubling the tuition subsidy for low-income students only increase average student surplus by an magnitude of one fourth as of removing the quota policy.

Our work contributes to the growing literature on the role of college admissions on educational inequality.[5] The literature documents vertical differentiation in students' backgrounds across colleges (i.e., students with higher socioeconomic status are more likely to

[3] A student–college pair (i, j) forms a blocking pair if college j admits at least one student whose score is lower than i and student i attends college with quality lower than j. The number of blocking pairs counts all the blocking pairs in the matching outcome.

[4] The degree of mismatch for a student is the difference in college quality between his matched college and the college he would attend under perfect assortative matching. The degree of mismatch of the whole matching outcome is the sum of absolute value of the degree of mismatch for each student.

[5] A recent literature survey on educational inequality, including higher education, can be found in Blanden et al. (2023).

present in high-quality colleges) and examines the effects of policy remedies (Goodman, 2008; Hoxby and Avery 2013; Dynarski et al. 2018; Dynarski, Page, and Scott-Clayton 2023; Andrews, Imberman, and Lovenheim 2020; Chetty et al. 2020). As we indicated, one source is differences from student-side. Low-SES students may underestimate the value of high-quality colleges when applying for colleges, due to behavioral bias and information gap (Dillon and Smith 2017; Dynarski et al. 2018; Hoxby and Avery 2013; Wu and Zhong, 2020; Wang, Wang, and Ye 2022). Another source is from college side, in particular, admission policies biased against students with low socioeconomic status by favoring athletes, legacy students, and children of faculty (Espenshade, Chung, and Walling 2004; Arcidiacono, Kinsler, and Ransom 2022). There is also a large branch of literature studying how affirmative action affects educational inequality (Arcidiacono 2005; Bagde, Epple, and Taylor 2016; Otero, Barahona, and Dobbin 2021). Regional admission quotas can be regarded as a special type of affirmative action that prioritizes students from certain regions.[6] Our paper contributes to the literature by considering both student- and college-side distortions affecting education inequality in college admissions. In particular, we find that policies changing college "price" (e.g., tuitions) seems matter less than "quantity" policies (such as quotas). Our paper is one of the first to highlight the importance of quota policy and elicit it as a market segmentation problem.

Our work also constitutes a new attempt of structural estimation on college admissions and matching markets. There are two approaches of estimating agent preferences in matching literature. One approach uses observed application or admission behavior of the participants to infer their preferences (see Arcidiacono 2005, Fu et al. 2022 on college admissions; Agarwal and Somaini 2018, Burgess et al. 2009, Hastings et al. 2009, He 2015 on public school choice). Another approach relies purely on the equilibrium matching outcomes to infer preferences (See Epple, Romano & Sieg 2006, Fu 2014 on college admissions; Agarwal 2015 on the Medical Match, Akyol and Krishna 2017 on public school choice, Boyd et al. 2013 on teachers' job match).[7] Our approach followed the second, i.e., identifying preference through equilibrium outcomes, by taking advantage of the unique feature of China's college admission system, i.e.,

[6] In a recent study, Yang (2023) also studies the policy implications of regional admission quotas, with a focus on labor migration and human capital distribution.
[7] Agarwal and Somaini (2020) provide a summary of econometric models for preference estimations in matching markets, including both approaches.

admissions based solely on student exam scores (subject to a quota system). The identification is methodologically and computationally simple, so that we can estimate each individual student's preference order for every college, and conduct a rich counterfactual analysis at individual student-college level.[8] Our model can be used for policy simulations for countries with a centralized college admissions system like China.[9]

Finally, our work also links to literature on matching under distributional constraints. Kamada and Kojima (2015) argue that a rigid quota system can lead to instable matching outcome *across* regions, and be improved through a flexible quota system allowing demand-driven reallocation among regions. In our counterfactual analysis, we test how a flexible quota system partially integrating the college market may improve matching equality.

This paper proceeds as follows: Section II introduces the institutional features of the *gaokao* system in China. Section III describes our data and variables. Section IV shows the stylized facts about matching inequality. Section V presents our conceptual model quantifying matching inequality (i.e., imperfect assortative matching). Section VI presents the econometric model and estimation results. Section VII presents the results of counterfactual analysis, and Section VIII concludes.

II. Institutional Features

2.1 Overview

China's college admissions system is a large market to allocate higher education resources to students. Table A1 (in the Appendix) gives an overview of the system. In 2009, our sample year, there were approximately 1,090 four-year colleges in the country, 10.2 million students

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[8] In general, the second (i.e., equilibrium) approach can be computational intense so that researchers have to divide the population into a small number of groups. For example, Epple et al. (2006) has to aggregate 768 colleges in sample into 6 groups, and students differ only in family income and ability, while Fu (2014) has to aggregate 673 colleges into 4 groups, and students are categorized only into 6 discrete types by ability and preference.

[9] Our method is close to several papers. Akyol and Krishna (2017) use the admission cutoff scores of high schools in Turkey to identify student choice set, yet they do not have individual student data but only score distributions in each school. Fack, Grenet, and He (2019) use the cutoff scores of 11 Paris public high schools as well as individual student data to identify student preferences on those schools. Otero et al. (2021) use cutoffs of college degrees in Brazil to estimate student preferences, and conduct counterfactual analysis on affirmative action.

took the *gaokao*, and approximately 30.5% of students were admitted to those colleges. From year 2009 to 2022, total admission rate has increased rather rapidly from 30.5% to 39.2%, but opportunities to enter high-quality colleges remain scarce. In China, there are 39 colleges that have received the Project 985 government designation and are acknowledged as the very top colleges, and 77 other colleges have received the Project 211 designation and represent the second-highest tier.[10] In 2009, the admissions rates to Project 985 and Project 211 colleges were 1.69% and 5.07%; there has been no increase in the admission rate of these high-quality colleges from year 2009 to 2022 (Table A1).

Given the fierce competition to enter high-quality colleges and the high stakes involved, there are long-standing debates about whether the admissions system is successful in achieving its stated goal: to allocate high-ability students to high-quality colleges. It has been found that matching outcome can be distorted by information friction or behavioral bias when students submit preference lists under the current system (Wang et al. 2022; Wu and Zhong 2020; Grenet et al. 2022). Partly because of those concerns, the system has been undergoing quite a few major reforms, such that switching from student preference-submission before exam to preference-submission after exam (Lien, Zheng, and Zhong 2016, 2017), switching from non-paralleled preference submission to paralleled one (Chen and Kesten 2017, 2019; Chen, Jiang, and Kesten 2020), etc.

2.2 Quota System

Another well-debated but less studied issue is the regional quota system imposed in college admissions.[11] While colleges are required to admit students within a region on a score priority basis, they still have a lot of choice when it comes to allocating quotas to each region. College may allocate more slots to local provinces. Chinese colleges are almost all publicly financed. Over 60 percent of their revenues are received from government, and among them, 70% are from provincial government (Liu, 2018). In fact, a large amount of colleges is administered by

[10] Attending these elite colleges is often associated with a high wage premium: prior literature estimates that attending Project 211 colleges improves the first-job wage by a range of 10 to 45% (Li et al. 2012; Jia and Li 2021).

[11] An exception is Li, Tan, and Xu (2014), who discuss four quota allocation methods including proportional quotas and others. The analysis is based on simulations using cutoffs and student distributions among several categories of colleges, without individual-level data or student preference estimations.

provincial government rather than the central government (i.e., the Ministry of Education). In addition, college may favor students from developed area, because those students are easier to adapt to college study and obtain degrees (Chan, Wang, and Zhao 2019).[12]

College preferences over local and rich students may be exacerbated by uneven geographic distribution of colleges. Table A2 shows the geographical distribution of high-quality colleges. High-quality colleges are concentrated in more developed East regions: these regions have 35% high-school graduates of all the high-school graduates in the country, but over 50% high-quality colleges according to the number of colleges. In contrast, Middle regions have 33% high-school graduates, but only 15% high-quality colleges.

Because of the regional quota system, the chances of attending higher-quality colleges are very different for students from different provinces. In Figure A1(in Appendix), we plot college admission rates in 2009 across provinces. The proportion of students attending high-quality colleges varies significantly among provinces. For example, the admission rate of Project 985 colleges in Shanghai exceeded 5%, while the admission rate in Henan was about 1%. The admission rate of the Project 211 colleges in Beijing is almost five times that of Guizhou province.

2.3 Admission Procedure and the Stability

China's *gaokao* system is a centralized college admission system, under which students are matched to colleges based on their performance in China's college entrance examination. Students choose from one of two tracks in high school: science or humanities. Each track has its own examination and admissions quotas.[13]

The admission process has four stages:

(1) *Colleges determine quotas*. Colleges set admission quotas for each track in each province separately. Therefore, each track in each province is a separate matching market.

[12] The regional quota system can be traced back to the imperial examinations in ancient China, which was almost the only channel to the rank of government official. As late as the Ming Dynasty, the government consciously allocated the number of admissions among regions, and often tilted in favor of underdeveloped areas (Ho, 1962).

[13] A small fraction of students is admitted to colleges via special channels, like the arts or sports track. Given the small share and data limitations of such tracks, our analysis focuses on the major two tracks.

(2) *Students participate in the gaokao*. Students take the *gaokao* on the scheduled days (typically in early June). The examination is organized by provinces, which may use the national examination questions or develop their own test questions.

(3) *Students submit their preferences*. In most provinces, students submit the rank order list of their preferred colleges after finding out their *gaokao* scores and percentiles in their exam-taken provinces. In some other provinces, students submit their preferences based on their estimated scores (after they have received the answer key but have not yet learned their exact scores). Only in very few provinces, students submit their preferences before taking the *gaokao*. Students can submit their rank order list including only a relatively small number of colleges.

(4) *Colleges admit students*. Each province adopts one of two admission rules: parallel preferences or nonparallel preferences. Under the parallel preference system, the admission process is similar to the Serially Dictatorship (SD), or equivalently, Deferred Acceptance (DA) mechanism. Students are ranked by *gaokao* score. For each student, in her submitted rank order list, the system allocates her the most preferred college which has empty slots after admitting students having higher score than her.[14] Under the nonparallel preference submission rule, the admissions process is similar to the Boston mechanism. Colleges first consider students who order them first and, among them, admit based on their scores. If there are still available quotas, colleges then consider students who rank them second. In our sample, only a few provinces adopt the nonparallel preference rule.

In this paper, despite of various imperfectness, we assume that matching outcome is stable under the system and use it as our key assumption for identification. First, China's system has been moving from a less stable mechanism (i.e., non-paralleled preference submission before exam) to a more stable one (parallel preference submission after exam). In 2009, 29 of all the 31 provinces have changed to preference-submission after exam and 17 have changed to

[14] Since students do not specify the preference order list for all colleges, the system deviates somewhat from the standard deferred acceptance (DA) mechanism, but the preference manipulation from students is still much smaller than non-truth-telling mechanisms (such as the Boston mechanism), and the stable matching is much easier to achieve (Chen and Kesten 2017, 2019; Chen et al. 2020).

paralleled submission.[15] Second, despite informational or behavioral bias, most students and parents can be sophisticated in preference submission enough such that the equilibrium matching outcome is close to stable, since they can learn from cutoffs of all colleges in previous years from various public sources, and be aided by teachers and professional agents. Finally, even if the matching outcome is unstable, since we only use an aggregate variable, i.e., cutoff scores, as our identification condition (detailed in Section V), the method is still reliable as long as the mismatch does not distort the cutoffs.

III. Data and Variables

3.1 Chinese College Student Survey (CCSS)

Our primary data source is the CCSS 2013, a survey run by Tsinghua China Data Center in year 2013. The survey was conducted by stratified random sampling based on colleges' geographical location (northeast, east, middle and west) and type (Project 985, Project 211 and lower-quality colleges). For each college, the survey randomly selected a group of students in their last year of four-year college education, most of them taking *gaokao* in 2009. The survey includes information about students' *gaokao* scores, high school tracks and college majors, college tuition paid and subsidies received, family background (household income, parental education), and residence. It totally sampled 65 colleges in China with over 10,000 individual samples. We conduct several data-cleaning steps and finally obtain a sample of 5,929 college students coming from 53 colleges in 30 provinces (4,723 science students and 1,206 humanities students).[16]

Table 1 shows the descriptive statistics of student characteristics and college attributes. Our sample contains students with diverse socioeconomic backgrounds, as indicated by the large

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[15] In a few provinces, the admission rule is close to the Boston mechanism, and the stability condition may not be satisfied. In our robust checks we re-estimate student utility function excluding students from these provinces and find similar results. See Section VI and Appendix F.

[16] First, we exclude from our sample 7 higher vocational colleges and 5 private colleges: they represent low-quality colleges, and public information about their admission cutoffs is not available. The remaining 53 colleges are distributed in 22 provinces and municipalities across China, covering different geographical regions. Among them, 24 are Project 211 colleges and 9 are Project 985 colleges. Second, we limit the sample to students who took the *gaokao* in year 2009. We also exclude students admitted through channels other than the science and humanities tracks. Finally, we exclude students with missing important information. Table A3 (in Appendix) presents the details of the sample construction.

standard deviations in family income and parental education. The net tuition paid is low relative to family income for the average student (less than 5%) but may be sizable for low-income households.

3.2 Administrative Data on College Admissions

The CCSS may not be a representative sample of all students and colleges in China's college admissions system. We complement the CCSS data with the nationwide Administrative Data on College Admissions in 2003. The administrative data contains the major track, *gaokao* scores, and admission outcomes of *all* students (including non-admissions) who took the *gaokao* in 2003 (6.2 million in total). It also contains individual information such as the student's gender, urban vs rural residence (*hukou*), and residential province.[17]

3.3 Data on Other College Characteristics

We measure college quality by college rankings, obtained from a book titled "*A Suitable University and Specialty for You*" (Wu 2009). The book has been widely used among *gaokao* students in choosing colleges. There are three types of college rankings in the book: college rankings in natural sciences, social sciences and overall rankings.

We collect the tuition fees of colleges from a book titled "*Gaokao Admission Cutoffs and Application Guidebook*" (Qiu and Zhao 2010) and the Internet.[18] Tuition fees vary by major, so we take the median of all major tuition fees at a college as its college tuition.

We collect the geographic longitude and latitude data of the city where each college and each student's family are located through the Baidu Map Open Platform. This information provides the linear geographical distance between the college and the students. We also collect the 2009 per capita GDP of the city where the college is located from the statistical yearbook of each province. Table A4 (in Appendix) shows descriptive statistics on the attributes of 500 four-year colleges included in Wu (2009) and used in our counterfactual analysis.

For the 53 colleges in the CCSS data, we collect the cutoff scores for each province and track in 2009 from the book "*National College Enrollment Score Compilation of the Year 2007-*

[17] Unfortunately, we are unable to obtain the 2009 administrative data. We use the available administrative data that is closest to the year 2009 instead. The quota and college quality distributions are relatively stable over time for most colleges.

[18] http://www.gaosan.com/

2009" (Tang 2010). The missing data are supplemented by a database from the Internet.[19]

3.4 Measuring Student Abilities

Student ability (or their pre-college human capital) is a key variable in our empirical analysis, yet it cannot be directly acquired in data. The observed *gaokao* score is directly comparable within a province, but not comparable across provinces because many provinces use different exam papers. We use two methods to convert the original *gaokao* scores into comparable student ability measures across provinces.

First, we use the within-province-and-track score *percentile* as the measure of student ability comparable across provinces (Chan et al. 2019).[20] The implicit view under the measure is that, even though there might be differences in individual education investment across provinces, students with the same within-province score rankings may have similar intrinsic abilities. This notion can be consistent with the educational equality objective embedded in the *gaokao* system, that is, to provide equal access to higher education resources for students with the same abilities, regardless of one's residence.

Second, we construct a measure of student pre-college human capital comparable across provinces, and use it to capture student ability. In the CCSS data, we observe both student *gaokao* scores and their college GPA. The former is comparable within a province, while the latter is comparable within a college. Intuitively, students with similar college GPAs from the same college provides a benchmark to compare *gaokao* scores across provinces. We formalize this intuition into a measurement model to identify the distribution of students' ability in each province (Cunha and Heckman 2008; Cunha et al. 2010). The details of student human capital construction are in Appendix B.

In Figure A2 (in Appendix), we plot the provincial distribution of pre-college human capital(θ^0), where provinces are ranked by averaged θ^0, i.e., $E_p(\theta^0)$. Provinces in the eastern region and economically developed provinces (such as Zhejiang and Jiangsu) usually have higher $E_p(\theta^0)$, while provinces in the western region and provinces with a higher proportion

[19] https://www.daxuecn.com/chaxun/
[20] We transform the 2009 raw *gaokao* scores (in CCSS 2013) into percentiles, by using the 2003 *gaokao* scores (in 2003 administrative data). The details of score transformation are in Appendix A.

of rural population (such as Gansu and Guizhou) have lower $E_p(\theta^0)$. [21]

IV. Evidence of Matching Inequality in China's College Admissions

We first present descriptive evidence on matching inequality in the current *gaokao* system, and highlight some institutional features (in particular, quota and subsidy policy) potentially affecting the admissions outcomes.

4.1 Socioeconomic Status and College Attendance

As we stated, matching equality in college admissions would empirically imply two things: First, high-ability students should attend high-quality (or commonly preferred) colleges. Second, student SES other than their ability should *not* impact which colleges they attend. We now examine whether this is true. We run the following regression in Equation (1):

$$College\_quality_i = \alpha + \beta * Ability_i + \gamma * SES_i + Track_i + Prov_i + \epsilon_i, \qquad (1)$$

where $College\_quality_i$ is the college quality attended by student i (a higher value implies a higher quality), $Ability_i$ indicates cross-province comparable student ability, measured as either the within-province-and-track score percentile or the human capital (θ^0), SES_i indicates students' socioeconomic status, including family income, parental education, gender, race, high school quality and *hukou*, $Track_i$ is a dummy indicating whether the student is in science or humanities track. The data source is CCSS 2013.

The regression results are reported in Table 2. Student ability (either score percentile or human capital) is still the strongest predictor of college quality students attend. This provides evidence that the positive assortative matching is largely obeyed. Second, SES variable are still jointly highly significant. In particular, family income, gender and attending elite high school are individually significant. The results provide strong evidence that students are not solely

[21] We verify the robustness of the estimates by examining the correlation of $E_p(\theta^0)$ with the average cognitive ability test scores of secondary school students in each province, surveyed in the 2010-2018 China Family Panel Studies (CFPS). Figure A3 (in Appendix) plots the two measures against each other. We find that the correlation coefficient between them is 0.548, which is significant at 1% level. CFPS is a national and comprehensive social tracking survey project that includes data at individual, family, and community level about Chinese society, economy, population, education, and health, conducted by Institute of Social Science Survey (ISSS), Peking University.

admitted by their abilities, and imperfect assortative matching may still exist.

Table A5 provides an alternative way to show the evidence of unequal matching. We compare the quality of colleges attended by students with different socioeconomic status, including family income, educational education and *hukou*, as well as their abilities. The difference in college qualities attended by students is much larger than the differences in students' ability.

4.2 Geographic Residence and College Admissions

The difference in college qualities attended by students with different socioeconomic status might be driven by students' geographic residence.[22] To see this, let us explore the coefficients of the provincial dummies, $Prov_i$, in our previous regression (Equation (1)), which reflect the difference in college quality student attended by provinces after controlling for students' ability and observed social-economic status.

The coefficients of provincial dummies are plotted in Figure 2. A student's residential province has great impact on the attended college quality given their ability and socioeconomic status, indicated by the large variation in province fixed effects. For example, other things equal, Beijing students attend colleges with a higher quality than the national median student by 0.2 (with a full scale of 1). Although the two measures of student abilities result in quite different provincial fix effect, the whole picture, i.e., residency matters, does not change.[23]

One possible reason why residency matters, as we indicated, is college quota policy, which may be unevenly allocated across provinces. We collect the quotas for the 53 CCSS-surveyed colleges in each province, and regress it on college and province characteristics as the following:

$$Q_{jp} = \alpha + \beta_1 HomeProv_{jp} + \beta_2 GDP_p + \beta_3 HomeProv_{jp} * GDP_p + \beta_4 X_p + \epsilon_{jp}, \quad (2)$$

where Q_{jp} is the quota of college j allocating to (students from) province p, normalized by

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[22] If we regard student score percentile within province as the proper measure of her ability, then the quota allocation should be proportional to the numbers of applicants of each province, and admission rate for each group of colleges with the same quality level should be the same among provinces. Then unequal admission rates (as shown in Figure A1) has already indicated the unequal quota distributions among provinces.

[23] Provinces that are "favored" in *gaokao* admission in terms of score percentile are often not "favored" in terms of human capital. This indicates that student score percentile and human capital may capture different aspects of student abilities, and polices based on each of these two student ability measures may induce different matching outcome.

the number of high school graduates in province p. $HomeProv_{jp}$ indicates whether college j is located in province p. GDP_p is GDP per capita of province p, and X_p includes other provincial characteristics.

Table 3 shows that the determinants of college quota allocation. As in Column (1), colleges allocate 1.292 more quotas per 10,000 students to students from home provinces. Since there are over 1,000 four-year colleges in the country, this would result in a total number of 1,300 quotas per 10,000, or 13% students. Colleges also allocate more quotas to economically developed areas. For each 10,000-yuan increase in provincial per capita GDP, each college's quota increases by 0.019 per 10,000 students. The largest regional gap of per capita GDP in 2009 is 60,000 yuan (between Beijing and Guizhou), which would induce a quota gap of 0.019*6*1,000=114 per 10,000, or 1.1% students. The “home-bias” of colleges in developed provinces is even stronger, as indicated by the coefficient of the interaction between home province dummy and per capita GDP in Column (2). This further widens the discrepancies in quota distributions between developed and undeveloped areas, given that colleges are concentrated in developed areas (as shown in Table A2).

Columns (3) -(4) and columns (5)-(6) show the results for below-median-quality and above-median-quality colleges, respectively. The “home bias” is common for both college groups, while low-quality colleges have a stronger preference for developed provinces than high-quality colleges.

4.3 Tuition Subsidies

Colleges also attract students using tuition subsidies including tuition waivers and scholarships. Although the gross tuition fees at public colleges are highly regulated and largely uniform, colleges can vary net tuitions by giving tuition subsidies to specific students. All colleges in our sample are public, and their average tuition fee varies between 3,500 and 6,000 yuan per year, accounting for 10-20% of per capita GDP in China. Colleges often provide students with merit-based scholarships and need-based tuition waivers (including financial aid) to reduce the cost of attendance. The subsidy policies can benefit students with disadvantaged socioeconomic status and promote the equalization of opportunities for higher education.

We estimate the tuition function using Equation (3):

$$y_{ij} = \delta_0 + \delta_1 Score_i + \delta_2\, ln(\, income)_i + \delta_3 ParentEdu_i + \delta_4 Male_i$$
$$+\delta_5 Rural_i + \delta_6 MedianTuition_j + \delta_7 Rank_j + e_{ij}, \qquad (3)$$

where y_{ij} represents tuitions or subsidies charged by college j to student i. We estimate Equation (3) separately for three different y_{ij}: merit-based scholarships, need-based tuition waivers, and net tuitions, which equal to each college's median tuition minus the scholarship and tuition waiver. Explanatory variables include two sets of variables: (i) student characteristics such as *gaokao* score percentile ($Score_i$), income ($ln(\, income)_i$), parental education ($ParentEdu_i$), gender ($Male_i$), and *hukou* ($Rural_i$) and (ii) college characteristics such as its median tuition ($MedianTuition_j$), college ranking from Wu (2009) ($Rank_j$).

Table A6 (in Appendix) shows the regression results. We find that the amount of scholarship is positively correlated with college entrance exam score, negatively correlated with family income. Tuition waivers are negatively correlated with family income and parental education. As the result, the net tuitions are negatively correlated with scores, and positively correlated with family income. In addition, female students and students with rural *hukou* are favored in the tuition policy.

All the evidences shown in this section suggest the existence of matching inequality in China's college admissions. To evaluate how different factors contribute to the unequal matching outcome, we need an equilibrium model on matching. In the next section, we detail our conceptual framework of such a model.

V. Conceptual Framework

In this section, we present a matching model between colleges and students. The model allows for students' heterogeneous preference order of colleges and a quota system segregating students into submarkets. We then construct our measure of matching (in)equality in college admissions, i.e., (imperfectness of) positive assortative matching (PAM), and discuss how we use these metrics to decompose the channels through which the matching inequality under current policy come from and evaluate counterfactual policies.

5.1 Environment

Consider a group of students indexed by $i \in \{1,2,\dots,I\}$, being matched to a set of colleges indexed by $j \in \{1,2,\dots,J\}$. Colleges have a priority over students based solely on their abilities, s_i, measured either by college exam score percentile or human capital. Students have preferences over colleges based on a strict ordering, $\succ_i$. The preferences depend on college attributes (college quality, location, etc.) and may be different for different students. In particular, students value two types of college attributes, q_j and Z_j. The first attribute, q_j, represents college quality, for which all students have the same rank ordering $\succ_q$. Z_j represents vectors of other college attributes, including location and tuition. Students have heterogeneous preferences for Z_j, leading to individual-specific preference order for colleges.

The market has a quota system: Students are segregated into different markets, $\psi(i) = p: I \longrightarrow P,\ p \in \{1,2,\dots,P\}$. In our setting, a market is a unique combination of province and track (science or humanities). In each market p, college j sets admissions quota $e_{jp} \geq 0$ and is subject to $\sum_p e_{jp} = E_j$, where E_j is the total enrollment capacity. Let $E = \{E_1, E_2, \dots, E_J\}$ denote the vector of the total quota and $e = \{\{e_{11}, e_{12}, \dots, e_{1P}\}, \dots, \{e_{J1}, e_{J2}, \dots, e_{JP}\}\}$ the set of quotas for each college and market.

The centralized admissions system applies a stable matching rule (e.g., deferred acceptance) separately for each market to match students to colleges. Let $\phi(\succ_i, s_i, e) = \varphi$ denote the matching function, such that $\varphi(i) = j$ if student i is admitted to college j, and $\sum_{i\in\{i:\psi(i)=p\}} 1(\varphi(i) = j) \leq e_{jp}, \forall j, p$; that is, for any college in any market, the number of admitted students is no larger than the specified quota. Because college priorities are based on a single index of students (i.e. exam scores), the assignment is unique and stable (Azevedo and Leshno 2016; Fack et al. 2019). The matching outcome can be characterized by the cutoff scores, $c_{jp}(\varphi)$, for each college j and market p, which is the minimum test score of admitted students (Azevedo and Leshno 2016):

$$c_{jp}(\varphi) = \min_{i\in\{i:\varphi(i)=j,\psi(i)=p\}} s_i,$$

and define $c_{jp}(\varphi) = +\infty$ if $e_{jp} = 0$.

Student i's' feasible choice set includes colleges having cutoffs lower than his score: $A_i = \{j \in J: s_i \geq c_{j\psi(i)}(\varphi)\}$. Let $b_i(\varphi) = \{j \in A_i | j \succcurlyeq_i k, \forall k \in A_i\}$ denote his most preferred option. The stability of the matching outcome (within a market) ensures that the assigned college is the most preferred college in his feasible set, i.e., $\varphi = b_i(\varphi)$. This stability condition is the foundation of our identification strategy in recovering students' preferences for colleges.

5.2 Measures of Positive Assortative Matching

Positive assortative matching (PAM) is defined as matching higher-ability students (i.e. with higher s_i) with higher-quality colleges (i.e. with higher q_j). We define two metrics to assess the level of imperfectness of (or deviation from) PAM for a matching outcome.

DEFINITION 1. Number of blocking pairs: $B(\varphi) = \sum_i \sum_j 1\{q_j > q_{\varphi(i)}\}\, 1\{s_i > \min_{\varphi(k)=j} s_k\}$.

Student–college pair (i, j) forms a blocking pair if college j admits at least one student whose score is lower than i (i.e., $1\{s_i > \min_{\varphi(k)=j} s_k\}=1$) and student i attends a college with quality lower than j (i.e. $1\{q_j > q_{\varphi(i)}\}$=1). PAM occurs when there are no blocking pairs. Blocking pairs are commonly used metrics in the matching literature to describe (in)stability (Calsamiglia et al. 2010, Lien et al. 2016). Note that the concept is different from stability w.r.t. student heterogeneous preference, which we always assume. We use the total number of blocking pairs divided by the number of individuals, $\bar{B}_i(\varphi)$, to make the measure easier to interpret. The details of calculating blocking pairs are in Appendix C.

DEFINITION 2. Non-directional degree of mismatch: $D(\varphi) = \frac{1}{N}\sum_{i=1}^{N}\left|q_i - q_i^{PAM}\right|$ and directional degree of mismatch: $D'(\varphi) = \frac{1}{N}\sum_{i=1}^{N}(q_i - q_i^{PAM})$.

In the definition, q_i is the quality ranking of college matched with student i in a certain matching outcome, and q_i^{PAM} is the quality ranking of college matched with student i under PAM. $D(\varphi)$ measures the degree to which a matching outcome deviates from a perfect matching. $D'(\varphi)$ measures whether a certain group of students is, on average, overmatched (with a positive value) or undermatched (with a negative value). This measure has been used by Wu and Zhong (2020), and the concept of overmatch and undermatch have been developed in Dillon and Smith (2017), in which they use the joint distribution of college quality and student ability quartile to identify the (coarse) mismatch.

5.3 Decomposition of Imperfect Assortative Matching

We compare the relative importance of heterogeneous preferences and the quota system in explaining the imperfect assortative matching by counterfactual simulations. Let $y(\varphi)$ denote either the blocking pair $\bar{B}_i(\varphi)$ or the degree of mismatch $D(\varphi)$ for matching φ. Let φ_f denote the (equilibrium) matching outcome under current policy in our data (i.e., CM in Figure 1). Then, $\varphi_f = \phi(\succ_i, s_i, e_f)$, where $e_f = \{\{e_{11f}, e_{12f}, \dots, e_{1Pf}\}, \dots, \{e_{J1f}, e_{J2f}, \dots, e_{JPf}\}\}$. The three elements of the matching function (ϕ) reflect the actual student presences, their scores (or abilities) and the actual quota policy, respectively.

Consider the following counterfactual scenarios:

1. *No heterogeneous preferences, existing quota policy*: $\varphi_a = \phi(\succ_q, s_i, e_f)$. The market clears assuming the current quota allocation, and all students share the same preference order ($\succ_q$) for colleges based solely on college quality q (i.e., M2 in Figure 1).
2. *No quota system, heterogeneous preferences*: $\varphi_b = \phi(\succ_i, s_i, E)$, where E is the collection of total quotas for each college. Under this scenario, all students are pooled in a single market and are matched to colleges subject to the total quota of each college, i.e., $\sum_i 1(\varphi_b(i) = j) \le E_j, \forall j$ (M1 in Figure 1).
3. *No heterogeneous preferences, no quota policy*: $\varphi_c = \phi(\succ_q, s_i, E)$. Under this scenario, we shut down the impacts of both heterogeneous preferences and the quota policy. The matching outcome is PAM.

By construction, $y(\varphi_c) = 0$ provides lower bound for the imperfectness of assortative matching. In addition, $y(\varphi_a) < y(\varphi_f)$. We also hypothesize that $y(\varphi_b) < y(\varphi_f)$. Therefore, $y(\varphi_f)$ (i.e., current policy) provides upper bound for the imperfectness of assortative matching. As a result, the distance of $y(\varphi_a)$ and $y(\varphi_b)$ from $y(\varphi_c)$ and $y(\varphi_f)$ provides information about whether the deviation from the PAM outcome is driven more by heterogeneous preferences or the provincial quota policy. If, for example, $0 = y(\varphi_c) < y(\varphi_b) < y(\varphi_a) < y(\varphi_f)$, i.e, matching corrected for quota policy ($y(\varphi_b)$ or M1) is closer to PAM than matching corrected for SES-reduced student preference ($y(\varphi_a)$ or M2), then the current imperfect assortative matching ($y(\varphi_f)$ or CM) is mainly driven by quota policy.

Understanding the sources of imperfect assortative matching is essential to evaluating the proposed policy changes to the current system. If the imperfect assortative matching is driven by heterogeneous student preferences due to their socioeconomic status, it cannot be alleviated by reforming the admissions system and probably can only be partially offset by tuition policy. In contrast, the provincial quota system represents a market segregation and can be corrected by reforming the admission system itself.

5.4 Counterfactual Policies

Using the framework described above, we could also evaluate other counterfactual policies, including changing quota allocations or SES-induced student preferences in other ways.

Proportional Quota. We consider an alternative quota policy, proportional quotas, under which colleges allocate their admissions quotas proportional to each province's total number of applicants (i.e., students enrolled in *gaokao*). Proportional quota policy can be justified if we believe student groups are all the same between different provinces, either by their abilities or preferences over colleges. Let I_p denote the number of students in market p and e_{jp} be the quota of college j to market p. The proportional quota is defined as:

$$\widetilde{e_{jp}} = E_j \cdot \frac{I_p}{\sum_m I_m} .$$

Deferred Acceptance with Partially Integrated Market (DA-PIM). A fully integrated market (i.e., completely removing provincial quota) may be politically controversial. We consider a transitional quota system, namely, the Deferred Acceptance with Partially Integrated Provincial Quotas, or Partially Integrated Market (DA-PIM). Under DA-PIM, each college retains, for each province, a proportion (e.g., 80%) of the quota allocated to it under the status quo (i.e. "guaranteed or reserved quotas"), and the rest quotas are free for allocation among students from any province (i.e. "flexible quotas"). The admissions for the flexible quotas are based on the candidate's ability comparable across all provinces. The reserved quota, if unused after local demand is satisfied, can also be allocated to students from any other provinces. Details of the DA-PIM algorithm are in Appendix D.

The DA-PIM algorithm has nice properties: we show, in Appendix D, that DA-PIM achieves student optimal stable matching respecting provincial (guaranteed) quota. In addition, students will truthfully report their preferences over colleges. Therefore, DA-PIM is the best transitional mechanism, in some sense, from segmented markets to a fully integrated market.

Subsidy and Distance Policies. College costs and financial aids are important for student decisions on college applications. We then consider two additional counterfactual scenarios. First, to decrease the impacts of student preference for net tuition fees on the matching outcome, we double the tuition subsidies received by students from low-income families, thereby reducing the net tuition fees for them. The counterfactual net tuition for middle- and high-income students remains unchanged.

Second, we consider a scenario where we shorten all the distances between colleges and students by half, which can be seen as equivalent to cutting transport costs in half. Because low-income and high-income students have different sensitivities to traffic distance, such a policy would have different effects on the preference orders of the two groups.

VI. Empirical Model

In this section, we specify our empirical model, which maps the student preference order for colleges in the conceptual framework to the data. The empirical model paves the way for quantifying the sources of matching inequality and evaluating various counterfactual policies.

6.1 Estimating Student Preferences for Colleges

Students have preferences for various college attributes, and these preferences can be heterogeneous and depend on students' socioeconomic characteristics. College attributes include college quality, its proximity to the student, net tuition, and location. Specifically, student i's utility for college j is

$$U_{ij} = \delta_{ij} + \varepsilon_{ij} = \beta_1 HomeProv_{ij} + \beta_{2,i} Distance_{ij} + \beta_{3,i} SciRank_j + \beta_{4,i} SocRank_j + \beta_{5,i} NetTuition_{ij} + \beta_6 \ln(GDP_j) + \beta_7 Middle_j + \beta_8 East_j + \varepsilon_{ij}\,, \quad (4)$$

where $HomeProv_{ij}$ is an indicator of whether college j is located in student i's home province. $Distance_{ij}$ is the distance between the student's hometown and the college-located city. Both variables capture the travel and cultural distances that students take into account when choosing colleges. College quality is measured as $SciRank_j$ and $SocRank_j$, which present the college rankings in natural sciences and social sciences. $NetTuition_{ij}$ is the median tuition of college j minus any merit-based scholarship or need-based subsidy that student i receives from college j. Finally, $\ln(GDP_j)$ indicates the per capita GDP (in logarithm scale) of the city where college j is located, which is a proxy for local job opportunities. We also add dummies for regions in which colleges are located, i.e., the Middle or the East (the default is West) to further control for college location differences. Finally, ε_{ij} represents idiosyncratic preference shocks and is assumed to be i.i.d. as extreme value type I. The definition and descriptive statistics of all variables included in the student utility function are given in Table 1.

Unlike the observables, $NetTuition_{ij}$ is unobserved for colleges that students do not attend. We impute $NetTuition_{ij}$ by first estimating the scholarship and tuition waiver that student i might receive if she attends college j by estimating Equation (3) separately for each college using enrolled students' information. We then calculate the net tuition using Equation (5):

$$\widehat{NetTuition}_{ij} = MedianTuition_j - \widehat{Scholarship}_{ij} - \widehat{TuitionWaiver}_{ij}. \tag{5}$$

We explain the construction of net tuitions in more details in Appendix E.

Motivated by the conceptual framework, we allow students to place different weights on college attributes. Specifically, we allow the following coefficient to be a function of students' characteristics:

$$\begin{aligned}
\beta_{2,i} &= \mu_{2,0} + \mu_{2,1}LowInc_i + \mu_{2,2}HighInc_i\,. \\
\beta_{3,i} &= \mu_{3,0} + \mu_{3,1}Science_i\,. \\
\beta_{4,i} &= \mu_{4,0} + \mu_{4,1}Science_i. \\
\beta_{5,i} &= \mu_{5,0} + \mu_{5,1}LowInc_i + \mu_{5,2}HighInc_i\,. \qquad (6)
\end{aligned}$$

First, we allow $\beta_{2,i}$, the preferences for distance, to differ by family income levels. We categorize student i's family income as low ($LowInc_i = 1$) if it is in the bottom 1/3 of the family income distribution and as high ($HighInc_i = 1$) if it is in the top 1/3 of the distribution. The baseline is the middle 1/3. Student-specific preferences for college quality are represented by $\beta_{3,i}$ and $\beta_{4,i}$. We allow them to vary with students' track (science or humanities). Finally, we allow students' sensitivity to net tuition to differ by family income. The parameters $\mu_{5,1}$ and $\mu_{5,2}$ measure how the price sensitivity of low- and high-income students differs from that of middle-income students, respectively.

We estimate the utility function of students by using the discrete choice model. Recall that A_i denotes the choice (or feasible) set of student i, which is the set of colleges of which cutoff score (for the province and track of student i) is lower than or equal to the student's college entrance exam score. For colleges j and k in student i's choice set, student i prefers college j to k if $U_{ij} > U_{ik}$. We can then compute the likelihood of choosing college j as

$$P(chosen_{ij} = 1) = \frac{exp\ (\delta_{ij})1(j \in A_i)}{\sum_{k=1}^{J} exp\ (\delta_{ij})1(k \in A_i)}, \tag{7}$$

where $chosen_{ij}$ is a dummy variable indicating that student i chooses college j and $1(j \in A_i)$ is a dummy variable indicating that college j is in i's choice set. We can then calculate the log-likelihood of the observed enrollment outcome as a function of the parameters and estimate the parameters using maximum likelihood estimation.

6.2 Identification

Our identification relies on the stability property of the matching outcome: the college that a student actually enrolled is her most preferred college in her choice set, which is all the colleges with lower cutoffs than her score (Azevedo and Leshno 2016; Fack et al. 2019). This property links observed admissions to underlying preferences, and pin down the preference coefficients.[24] In our data, we observe rich variations in student characteristics, such as income level, track and the distance between their hometown and college. The admission results of students with similar choice sets (test scores) but different characteristics help identify the heterogeneous preferences for the same college attributes.

In addition, we argue that the estimates of the price coefficient, i.e. the preferences for net tuition, are unlikely to be biased due to unobserved college quality, a common issue in other consumer products markets. In our setting, all colleges are public and highly subsidized by the government regardless of their quality. As a result, raw tuition and subsidies are unlikely to be correlated with college quality. We verify this fact by examining the correlation between net

[24] In our data, we also observe the (incomplete) submitted rank ordering for colleges for some students. We choose not to use this extra information, because it may have large measurement errors and it definitely is not truth-telling. The previous literature shows that estimation based on the matching outcome, as opposed to the submitted rank orderings for colleges, is robust (Fack et al. 2019; Artemov et al. 2023).

tuition and observed college quality measures. Figure A4 (in Appendix) shows that there is no statistically significant correlation between net tuition and various quality measures.

6.3 Estimation Results

Table A7 (in Appendix) shows the choice set of students with different score percentiles. Students with higher scores have a larger choice set. Students in the top 20th percentile of the score distribution face a choice set approximately three times larger than that of students in the bottom 20th percentile of the score distribution.

The estimated student preferences for college attributes are shown in Table 4. In column (1), we show the estimates assuming that all coefficients do not vary by student characteristics. We find that students have strong home bias: the average benefit of attending a local college translates to an approximately 23,813 RMB yuan reduction in net tuition.[25] In addition, students prefer colleges with higher quality in natural sciences and social sciences, and they prefer colleges in economically developed regions and eastern regions.

Column (2) shows the estimation results taking into account of student heterogeneous preference for colleges. We find that, compared to middle-income students, students with low family income have a stronger negative preference for distance while students with high family income are less sensitive to college proximity. Students taking *gaokao* in science track prefer colleges with higher rankings in natural sciences, compared to students in humanities track, while their preference for colleges' social science rankings is lower. Low-income students have a negative preference for net tuition that approximately triples that of high-income students.

The model fits the data well. We use the estimated preference to allocate students using the deferred acceptance mechanism, and compare the mean of several college attributes (e.g., net tuition, quality rank, distance from home) using the actually attended colleges and predicted attended colleges for various student groups. Table A8 (in Appendix) shows that two values are very close to each other, indicating a good model fit. We also show that the baseline estimation results are robust if 1) changing net tuition estimation methods; 2) correcting potential

[25] By normalizing the coefficient of $NetTuition$ to 1, we can measure the change in monetary utility caused by the change in each college attribute. For example, the average benefit of attending a local college translates to an approximately 23,813 yuan reduction (=3.191/0.134*1,000) in net tuition.

estimation bias caused by the unstable matching mechanisms, and 3) adjusting for sampling bias. Appendix F shows the details of conducting robust checks, and Table A9 (in Appendix) reports the results.

VII. Counterfactual Analysis

In this section we present counterfactual analysis based on our estimation model.

7.1 Sample Construction and Simulation Procedure

Sample Construction. In our counterfactual analysis, we want to evaluate policy changes affecting the college admissions system *as a whole*. Unfortunately, CCSS data capture a possibly biased sample of all students and colleges in China. In particular, it only contains students admitted by colleges but not students unadmitted. Policies may change the extensive margin of college admissions: students not admitted under one policy may get admitted under another. Therefore, a national representative sample is indispensable.

We first construct a student sample representing all college applicants, either admitted or non-admitted, by combining data from CCSS 2013 and administrative data in 2003. The details are in Appendix G.1. The descriptive statistics of students' scores and socioeconomic characteristics in this generated sample are shown in Table A10 (in Appendix). Compared with CCSS 2013 sample, the simulated student sample has more male, less science-track and similar rural students, with lower parental income and education. The mean of score percentile is close to its ideal value of 0.5 but less than the value in CCSS (0.75), indicating that it is a representative sample of all students. In our counterfactual analysis, we assume that the utility obtained by not being admitted by any college is lower than entering any of the 500 colleges and is at the same utility level for each student.

We also construct a college sample representing all four-year undergraduate colleges. The sample contains, among all the 639 four-year undergraduate colleges in China, 500 colleges of which quality rankings are available in Wu (2009). The details are in Appendix G.2.

Simulation Procedure. We are now ready to deliver our results for counterfactual analysis. In each of our counterfactual scenario, the simulation procedure is the following: 1) We generate student preference orders over colleges based on the estimated student utility functions in Equation (4), taking into account of student preference assumptions specified for this scenario (homogeneous vs. heterogeneous preferences)[26]. 2) We then match students with colleges by the Serial Dictatorship (SD) mechanism[27], taking into account of the quota system specified in the scenario. In particular, under the current or proportional quota system, matching is conducted within provinces and tracks. Under the no provincial quota system, matching is a nationwide (but still within-track) system, where college preference for students is based on one of the two measures of student abilities comparable across provinces.[28] The matching procedure for partially integrated market is in Appendix D.

7.2 Decomposing Sources of Matching Inequality

Table 5 show our main results on matching inequality under counterfactual scenarios. In each scenario, we rank students either by within-province-and-track percentile (Columns (1) and (2)), or pre-college human capital (Columns (3) and (4)). We measure matching inequality, or imperfectness of assortative matching, using either the average number of blocking pairs (BPs) per student ($\bar{B}_i(\varphi)$), or the average degree of mismatch (DM, non-directional, $D(\varphi)$).

Table 5 Panel A shows results on decomposition of imperfect assortative matching. Four scenarios are included: the benchmark (heterogeneous preferences and status quo provincial quota, CM), PAM (homogenous preferences and no provincial quota restriction), and two middle cases: no provincial quota with heterogeneous preferences (M1), current quota with homogenous preferences (M2). Under the PAM (homogenous preferences and no provincial quota restriction), the number of blocking pairs is zero by construction.

We find that the imperfect assortative matching under current policy is driven by both the provincial quota system and students' heterogeneous preferences, indicated by the large change in BPs or DM in the two middle cases. Take Column (1) as an example. It shows that under the

[26] The baseline scenario is based on the *predicted* student utilities under the current policy, such that we can partial out the impact of the idiosyncratic shocks. It differs from the observed matching outcome because of those idiosyncratic shocks.

[27] When colleges have the same preference over students based solely on their score rankings, the SD mechanism is equivalent to the deferred acceptance mechanism.

[28] Students may have the same value of student abilities under either measure. In this case, we use the following tiebreakers to determine their admission priority: (1) If the two students come from the same province, the student with higher score for the "comprehensive" subject is given higher priority, to reflect the practice in reality; (2) If the two students come from different provinces, priority is given to the province with a lower GDP per capita.

current policy, the average number of blocking pairs per student is about 74. It decreases to 18.5 (by 75%) when the quota system is removed while heterogeneous preferences are retained (Row (2)), and it decreases to 32.5 (by 56%) when the quota system is retained while preference heterogeneity is removed (Row (3)). Similarly, Column (4) shows that under the current policy, the average degree of mismatch per student is about 60 (out of all 500 colleges). It decreases to 24.3 (by 59%) when the quota system is removed while heterogeneous preferences are retained (Row (2)), and it decreases to 49.3 (by 17%) when the quota system is retained while preference heterogeneity is removed (Row (3)). In three out of four specifications, i.e., Column (1), (2) and (4), we find that the reduction is larger when the provincial quota system is removed than when the heterogeneous preferences are removed. In summary, both factors play a role in explaining the imperfect assortative matching, but the quota system often plays a larger role than heterogeneous preferences.

Table 5 panel B shows the effect of other counterfactual policies on imperfect assortative matching. First, we find that proportional provincial quota policy (Row (5)) may or may not improve the assortative matching, depending on how student abilities are measured. Second, the partially integrated market is effective in improving the matching equality. Specifically, Row (6) shows that even with 20% of current quota allocate being freed up, the number of BPs is reduced by 34%-75%, and the average degree of mismatch is reduced by 32%-55%. Table A11 (in Appendix) shows the results of partially integrated markets with different proportions of flexible quotas.

On contrary, we find that the two policies modifying SES-induced student preferences, i.e., the subsidy and distance policies, have little impact on correcting imperfect assortative matching. Rows (7) and (8) show that the average number of BPs and the average degree of mismatch under these two policies is close to that under the current policy. In row (9), we further eliminate the heterogeneous preferences of students for net tuition and distance, and only retain student preferences for college quality and home preferences. We find that the degree of imperfect assortative matching is close to benchmark scenario. The result indicates that students care about college quality much more than college costs (at least when they are reasonably low), and students' home preferences play a dominant role in determining the matching outcome among factors inducing heterogeneous preference.[29]

Impacts on Different Student Groups. Counterfactual policies may affect the matching outcome of different student groups differently. We use the directional degree of mismatch to compare the matching outcomes for students with different socioeconomic backgrounds.

Table A12 (in Appendix) shows the average degree of mismatch (directional, $D'(\varphi)$) of different demographic groups under each policy. There are three major findings. First, we find that under the baseline scenario, the average degree of mismatch is small for either the socioeconomically disadvantaged or advantaged students: the average degree of mismatch of each demographic group is less than 6 out of all 500 colleges. Second, removing provincial quota alone can correct most of the mismatch, while 20% integrated market policy can also achieve a substantial reduction in the mismatch for both the socially advantaged and disadvantaged group. Third, the tuition and distance policy helps the socioeconomically disadvantaged students to attend colleges with higher qualities (as intended), while the magnitude is rather small. The results are consistent with our previous findings that imperfect assortative matching is mainly driven by quota restrictions, and if only taking heterogeneous preferences into account, imperfect assortative matching is mainly induced by attending colleges in home province, rather than preferences for tuition and geographic distance.

Additional Evidence on Matching Equality. Remember that matching equality implies immunizing the matching outcome from the influence of student SES. Under the current system, this goal has been shown not achieved (Table 2). Table A13 (in Appendix) report the results how matching outcomes may be affected by student SES under various counterfactual policies, as an epilogue of Table 2. As a whole, the results suggest that various counterfactual policies, except for the proportion quota, do not worsen matching inequality, indicated by the joint insignificant of the SES variables. The subsidy and distance policy even tend to improve the matching equality, indicated by an even lower joint significant of SES variables.

[29] In all counterfactual scenarios, students moving into or out of the market, i.e., students at the extensive margin, account for less than 6% of all students (not reported in tables). This may suggest the extensive margin may not play an important role on matching outcome, at least compared with students at intensive margin.

7.3 Policy Effects on Student Welfare

Our measure for imperfect assortative matching may not fully reflect the consequences of alternative college admissions systems on student welfare. In this subsection we evaluate effects of various policies on improving student welfare. We consider five counterfactual policies: 1) removing provincial quota, 2) implementing proportional quotas, 3) releasing 20% quotas, 4) doubling tuition subsidies for low-income students, and 5) reducing travel distances by half.

Changes in Student Welfare. Table 6 shows the aggregate welfare change from the current policy to five counterfactual policies. The welfare measure is the compensating variation calculated from the utility function under each counterfactual policy and the current policy. Column (1) shows the results of using within-province-and-track percentile as the admission priority. We find that proportional quotas would reduce the average student surplus by 17,859 yuan. This negative surplus is mainly caused by students who prefer colleges in their home province being forced to attend colleges in other provinces.[30] The 20% integrated market policy would increase the average student surplus by 3,212 yuan, and completely removing provincial quota (i.e. fully integrated market) would increase the average student surplus by 3,535 yuan. Column (2) shows the results using pre-college human capital as the measure of student ability. The proportional quota policy still has a large negative impact on the average welfare of students, while the impact of 20% and fully integrated market policies are minimal but still positive. Note that neither policy would require explicit government expenditure.

Subsidy policy and distance policy also increase the average student surplus. In Column (1), the subsidy policy doubling the tuition subsidy for low-income students could increase the average student surplus by 972 yuan. The cost of this policy is equivalent to 183 yuan per student. In other words, the net benefit of the policy is approximately 789 yuan. Reducing the travel distance by half would produce a similar increase in student surplus, though the cost of this policy is harder to evaluate. Column (2) shows that using human capital to measure student abilities can yield similar welfare implications.[31]

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[30] To verify the source of this welfare loss, we further shut down the impacts of students' preference for home-province colleges by setting its coefficient to zero. The average surplus change from proportional quotas is much smaller (-1,400 Chinese yuan) relative to the baseline.

[31] For the subsidy and distance policies, we further break down the surplus change into a price effect and an allocation effect. The price effect is calculated as the difference in student surplus when students

Not all the students are better off under counterfactual policies. However, under most counterfactual policies (except for proportional quota policies), the number of better-off students is greater than the number of worse-off students. Figure A5 further reports the average SES characteristics of better-off and worse-off students. Figure A5 Panel A, B and C shows the average family income, parental education years, and proportion of urban *hukou* of the better-off and worse-off student groups respectively. Students experiencing utility increase have, on average, lower family income, lower parental education, and less likely to be urban residents. This implies that the counterfactual policies can improve the welfare of socioeconomically disadvantaged students.

Changes in Wages. We also show the effects on wages of various policies. Wages are reported in the CCSS survey data and measured as the highest wage offer received when students graduated from the college. We predict students' counterfactual wages if they are admitted to a different college by estimating the wage equation using the actual students admitted to the college. The predictors include college quality, student ability, and the interactive terms of the two. The regression results are shown in Table A15 (in Appendix).

The results in Table7 suggest that the policy of removing provincial quotas have small but positive results on averaged student wage, with an increase of 1%. The effects of other polices are mostly positive, except for the subsidy and distance policy using the human capital as the measurement of student ability, which are negative but with a very small magnitude.[32]

VIII. Conclusion

Matching inequality in college admission exists in the Chinese *gaokao* system. We find that students from higher socioeconomic status and certain provinces are more likely to attend better-quality colleges, conditional on their college entrance exam performance. We estimate

enrolled in the same colleges as in the benchmark but face different tuition costs or travel distances. The allocation effect is calculated as the difference in student surplus between being enrolled in the benchmark and in the simulated college, given that students face counterfactual tuition costs (or travel distances). The calculation details are in Appendix H. Table A14 (in Appendix) shows that the surplus change from the two policies comes almost entirely from the price effects.

[32] The results that PAM-favored policies also increase average wages of graduated students suggest that student abilities and school qualities can be complemental. There is some evidence (but not much) in literature supporting this complementarity (e.g., Dillon and Smith 2020).

and show that both heterogeneous preference of students on colleges and uneven distribution of admissions quotas across provinces play an important role in explaining the imperfect assortative matching, a measure of matching inequality. Reforming the current provincial quota system in a proper way would significantly correct the imperfect assortative matching. Such policies can also benefit disadvantaged students and increase the overall student welfare.

These results have significant policy implications. In China, college admissions system has been widely acknowledged as a social equalizer, and attending elite colleges is one of the most important channels for upward social mobility. Our works suggest that the current system may still have a large space to improve itself. We highlight provincial quota system as a reform agenda. Even if a radical elimination of the provincial quota system is not possible, a gradual reform by partially integrating the market has great help.

Throughout the paper, we take a static view on the allocative effects of college admissions. College admissions system may have long-term impacts on labor market and social mobility. Unfortunately, our data are restricted to short-term outcomes and limit our ability to measure the welfare consequence of these policies for the long term. More empirical analysis is needed in this direction. Furthermore, pre-college human capital investment is not predetermined in life cycle and is a dynamic decision happening along long-time horizons before entering colleges. Pre-college human capital investment may also exhibit large differences across students' socioeconomic and geographic backgrounds, exacerbating the inequality in college admissions and social mobility that we document here. More research is needed to understand the interaction of pre-college human capital investment and the college admissions mechanism.

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Figures and Tables

Figure 1 Comparing Matching Outcomes

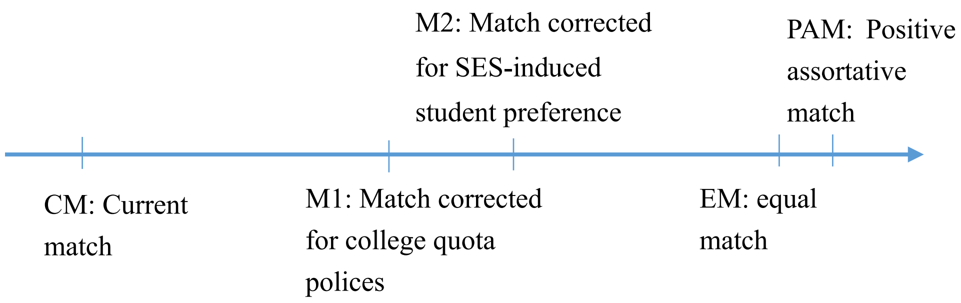
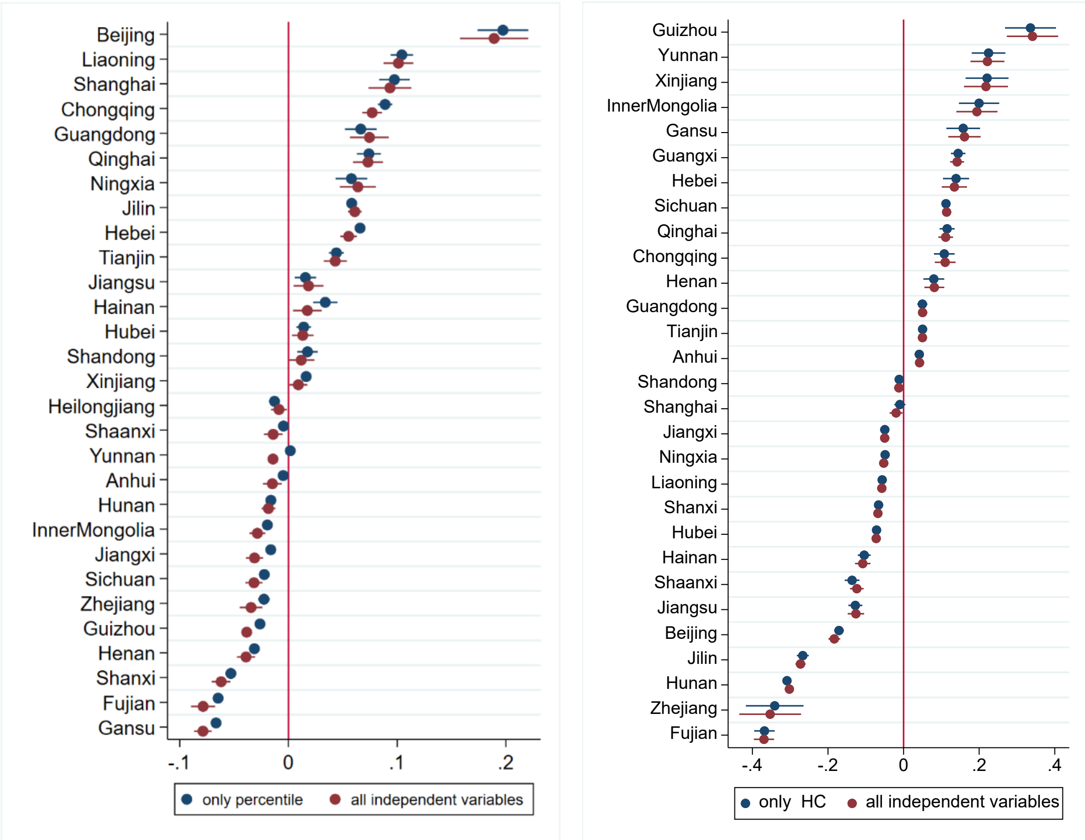


Figure 2. Impact of Students' Home Province on Admission Results

Panel A Score Percentile   Panel B Human Capital



Note: Coefficients of the provincial fixed effects and their 95% confidence intervals in Regression of Equation (1) and Table 2. The coefficients in panel A are from the regression results in column (1), while the coefficients in panel B are from the regression results in column (2). Blue dots correspond to the regression in which the independent variables exclude student socioeconomic characteristics, and red dots correspond to the regression including all the independent variables. The default group is Guangxi in panel A and Heilongjiang in panel B. Positive coefficients suggest that students from these provinces are more likely to attend high-quality colleges after other factors are controlled for.

Table 1. Summary Statistics of Student and College Characteristics

Variables	Definition	Mean	Std
Student characteristics (Obs = 5,929)			
Male	male = 1, female = 0	0.555	0.497
Rural	agricultural *hukou* = 1, nonagricultural *hukou* = 0	0.528	0.499
Minority	minority = 1, nonminority = 0	0.074	0.262
Science	high school track, science = 1, humanities = 0	0.797	0.403
Highsch	elite high schools above prefecture cities = 1, others = 0	0.548	0.498
Family income	sum of parents' annual income (unit: 1k RMB)	75.632	120.992
Parental education	highest year of parental education	11.308	3.473
Score percentile	within-province-and-track score percentile	0.752	0.206
College attributes that vary with individual (Obs = 5,929)			
Home province	whether the student attends college in home province	0.610	0.488
Distance	linear distance between college and student (1000 km)	0.471	0.602
Total tuition	actual total tuition paid by student (1k RMB)	5.760	4.429
Scholarship	merit-based scholarships offered by college (1k RMB)	0.956	1.854
Tuition waiver	need-based tuition waiver offered by college (1k RMB)	0.642	1.336
Net tuition	median tuition - scholarship - tuition waiver (1k RMB)	3.705	2.462
College attributes that do not vary with individual (Obs = 53)			
Total rank	standardized overall ranking of Chinese colleges	0.678	0.275
Sci rank	standardized natural science ranking of college	0.687	0.283
Soc rank	standardized social science ranking of college	0.661	0.259
College 985	985 college = 1, others = 0	0.170	0.379
College 211	211 college (including 985) = 1, others = 0	0.453	0.503
Median tuition	median tuition fees of each college (1k RMB)	5.285	0.837
Ln(GDP)	2009 ln(GDP) of the city where the college is located	8.382	0.981
West	whether the college is in western region	0.245	0.434
Middle	whether the college is in middle region	0.189	0.395
East	whether the college is in eastern region	0.566	0.500

Note: Student characteristic variables and individual-specific college attributes come from CCSS 2013 data (except for the distance, which comes from Baidu Map). The overall ranking, natural science and social science ranking of colleges come from Wu (2009). GDP data come from the 2009 statistical yearbooks of each province.

Table 2. Determinants of Student Attended College Quality

Dependent variable: College quality ranking		
	(1)	(2)
Score percentile	0.589***	
	(0.08)	
Human capital		0.657***
		(0.078)
Ln(family income)	0.031***	0.023*
	(0.01)	(0.012)
Parental education	0.018	0.005
	(0.02)	(0.018)
Male	0.039***	0.024*
	(0.01)	(0.014)
Minority	0.007	0.004
	(0.01)	(0.008)
Rural	-0.011	-0.008
	(0.01)	(0.013)
Elite High School	0.033***	0.031***
	(0.01)	(0.010)
Joint significance of socioeconomic var. (p-value)	0.002	0.008
Track FE	Yes	Yes
Province FE	Yes	Yes
N	5,095	5095
R^2	0.557	0.549

Note: Data source is CCSS 2013. Standardized beta coefficients. Standard errors are in parentheses and calculated by clustering over provinces; * p<0.1, ** p<0.05, *** p<0.01. College rankings are from Wu (2009).

Table 3. Determinants of College Provincial Quotas

	Dependent variable: College–province quota/number of provincial high school graduates (one in 10,000)					
	All colleges		Low-quality		High-quality	
	(1)	(2)	(3)	(4)	(5)	(6)
Home province	1.292***	0.164	1.570***	-0.214	1.003***	0.464
	(0.281)	(0.444)	(0.371)	(0.396)	(0.247)	(0.534)
GDP per capita	0.019**	0.004	0.028***	0.007	0.011	0.003
	(0.008)	(0.006)	(0.010)	(0.004)	(0.010)	(0.008)
Home province* GDP per capita		0.286**		0.459***		0.135
		(0.135)		(0.113)		(0.137)
Minority proportion	0.010**	0.007*	0.010**	0.008***	0.009	0.007
	(0.004)	(0.004)	(0.005)	(0.003)	(0.006)	(0.006)
Average education	0.010	0.001	0.010	-0.008	0.012	0.008
	(0.016)	(0.012)	(0.018)	(0.009)	(0.018)	(0.017)
Constant	-0.161	-0.005	-0.183	0.080	-0.143	-0.074
	(0.171)	(0.112)	(0.192)	(0.095)	(0.185)	(0.160)
N	1,590	1,590	810	810	780	780
R^2	0.415	0.494	0.452	0.593	0.400	0.430
Dep mean	0.068	0.068	0.071	0.071	0.065	0.065
Dep std	0.370	0.370	0.433	0.433	0.290	0.290

Note: The quota allocation of colleges in each province is from CCSS 2013, and the number of provincial high school graduates is from the China Social Statistics Yearbook. The criterion for dividing low-quality and high-quality colleges is whether the college quality ranking is above the median. Standard errors are clustered at the province level and shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 4. Student Preference Estimations

	(1)	(2)		(1)	(2)
Proximity			**Tuition**		
Home province	3.191***	3.201***	Net tuition	-0.134***	-0.129***
	(0.051)	(0.052)		(0.011)	(0.018)
Distance	-0.517***	-0.562***	Net tuition×LowInc		-0.065***
	(0.040)	(0.055)			(0.024)
Distance×LowInc		-0.028	Net tuition×HighInc		0.068**
		(0.069)			(0.027)
Distance×HighInc		0.191***			
		(0.069)	**Region economy**		
Ranking			ln(GDP)	0.245***	0.232***
Sci rank	2.263***	0.341*		(0.028)	(0.028)
	(0.151)	(0.189)	Middle	-0.345***	-0.364***
Sci rank×science		2.600***		(0.062)	(0.062)
		(0.152)	East	0.285***	0.266***
Soc rank	0.833***	1.594***		(0.057)	(0.057)
	(0.149)	(0.230)			
Soc rank×science		-1.025***	College type	control	control
		(0.211)	N	160,070	160,070

Note: The data source is CCSS 2013. The independent variable in Column (1) contains only college attributes, and the independent variable in Column (2) contains the interaction between college attributes and student characteristics. Standard errors are in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Table 5. Matching Inequality

Scenario		Score Percentile		Human Capital	
		# of BPs	Degree of mismatch	# of BPs	Degree of mismatch
		(1)	(2)	(3)	(4)
Panel A Decomposing source of imperfect assortative matching					
(1)	Current quotas with heterogeneous preferences (Benchmark)	73.47	37.94	171.59	59.55
(2)	No provincial quota with heterogeneous preferences	18.51	23.87	17.61	24.28
(3)	Current quotas with homogeneous preferences	32.45	17.78	136.30	49.25
(4)	No provincial quota with homogeneous preferences(PAM)	0.00	0.00	0.00	0.00
Panel B Other counterfactual policies					
(5)	Proportional quotas with heterogeneous preferences	34.92	23.23	222.62	62.06
(6)	20% integrated market with heterogeneous preferences	48.36	25.86	42.85	26.99
(7)	Current quotas with subsidy policy	73.38	37.79	171.56	59.51
(8)	Current quotas with distance policy	73.23	37.49	171.36	59.29
(9)	Current quotas with home preferences only	73.10	37.04	171.51	57.97

Note: Data source is the generated college applicants sample and generated college sample described in Section 7.1 and Appendix G. The total number of students is 62,140, and the total number of colleges is 500. Matching inequality is measured by the number of blocking pairs (BPs) and the degree of mismatch, in which student ability is measured by within-province score percentile or constructed human capital.

Table 6. Changes in Student Welfares

Counterfactual Policies	Change in average student surplus (1k yuan)	
	Within-province Score Percentile	Human Capital
	(1)	(2)
Proportional Quotas	-17.859	-17.848
20% Integrated Market	3.212	0.153
No Provincial Quota	3.535	0.219
Subsidy Policy	0.972	0.954
Distance Policy	0.681	0.680

Note: Data source is the generated college applicants sample and generated college sample described in Section 7.1 and Appendix G. The total number of students is 62,140, and the total number of colleges is 500. Welfare change is measured by the change in the utility under each counterfactual policy relative to the matching outcome under current policy, transformed into monetary values through dividing by the tuition coefficient in the demand estimation.

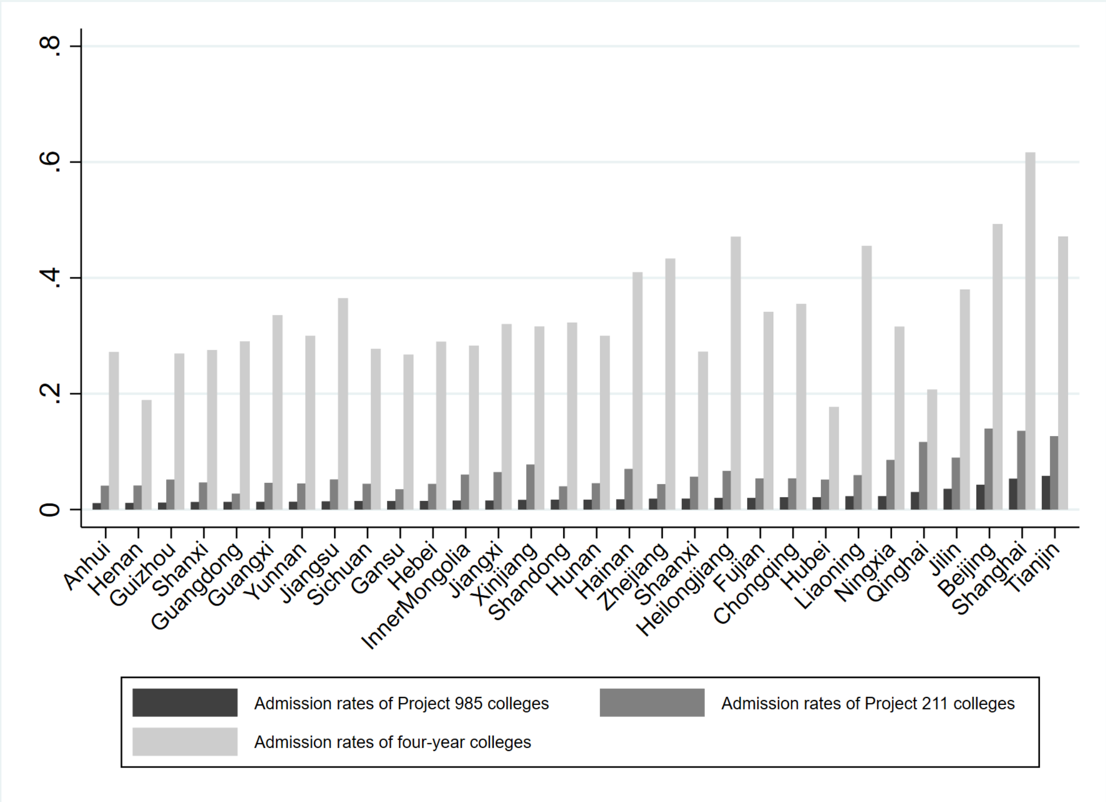
Table 7. Changes in Wages

Counterfactual Policies	Change in average student wage			
	Within-province Score Percentile		Human Capital	
	Δ (1k yuan)	%Δ	Δ (1k yuan)	%Δ
Proportional Quotas	0.057	1.64%	-0.010	-0.29%
20% Integrated Market	0.052	1.52%	0.047	1.36%
No Provincial Quota	0.057	1.65%	0.050	1.44%
Subsidy Policy	0.035	1.00%	0.000	-0.01%
Distance Policy	0.036	1.03%	0.000	-0.01%

Note: Data source is the generated college applicants sample and generated college sample described in Section 7.1 and Appendix G. The total number of students is 62,140, and the total number of colleges is 500. This table represents the changes in average student wages under each counterfactual policy relative to the current policy, as well as the percentage of changes. The average wage for students under benchmark situation is 3.459 k yuan/month.

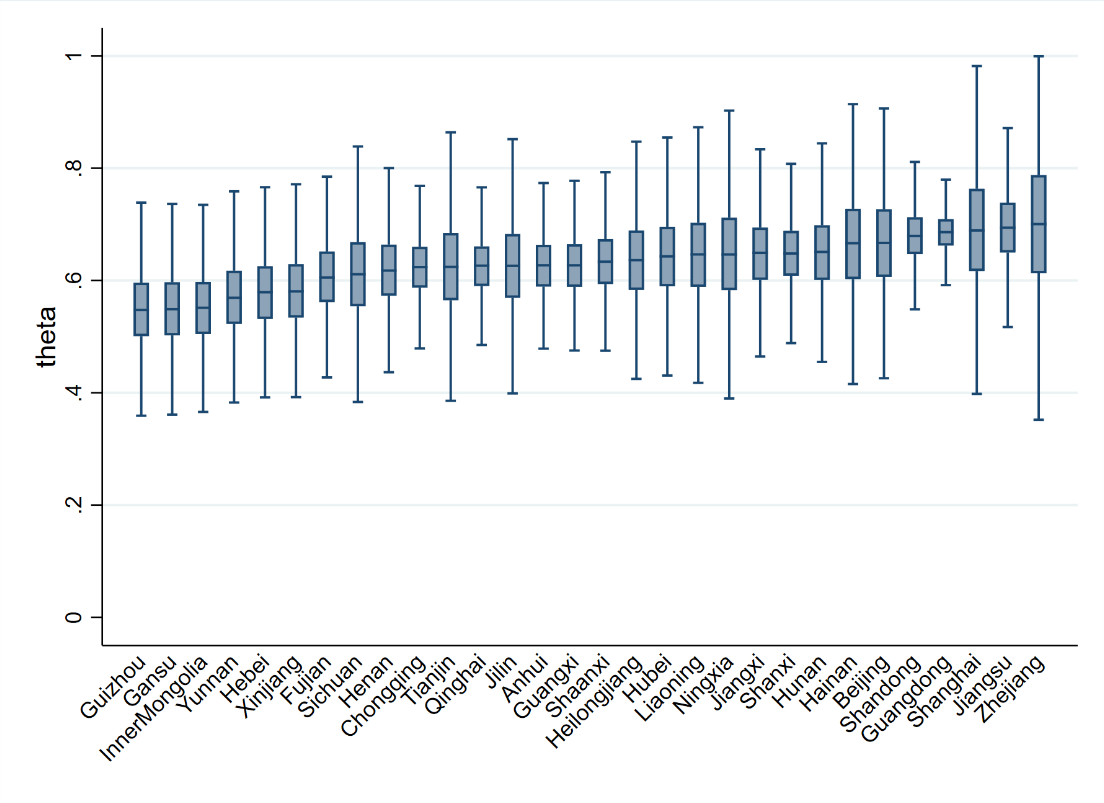
Appendix Figures and Tables

Figure A1. College Admission Rates across Provinces (Year 2009)



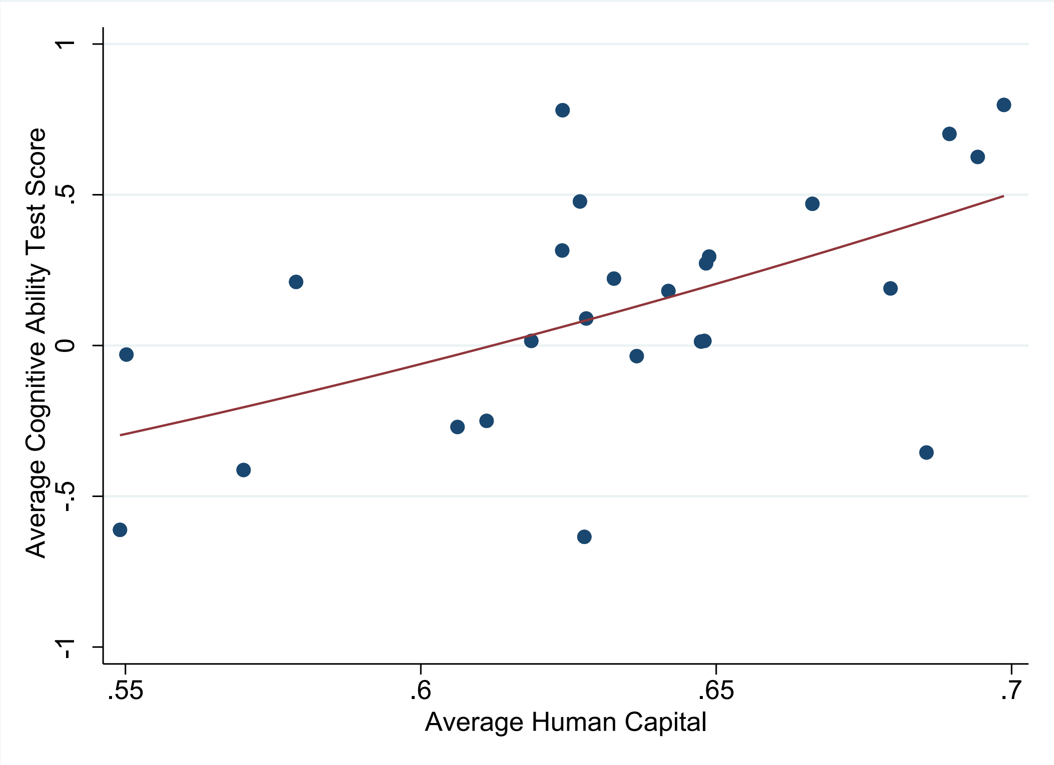
Note: Data are collected from the internet https://www.gov.cn/. Provinces are ranked from low to high according to the admission rate of the project 985 colleges.

Figure A2. Distribution of Pre-College Human Capital (by Province)



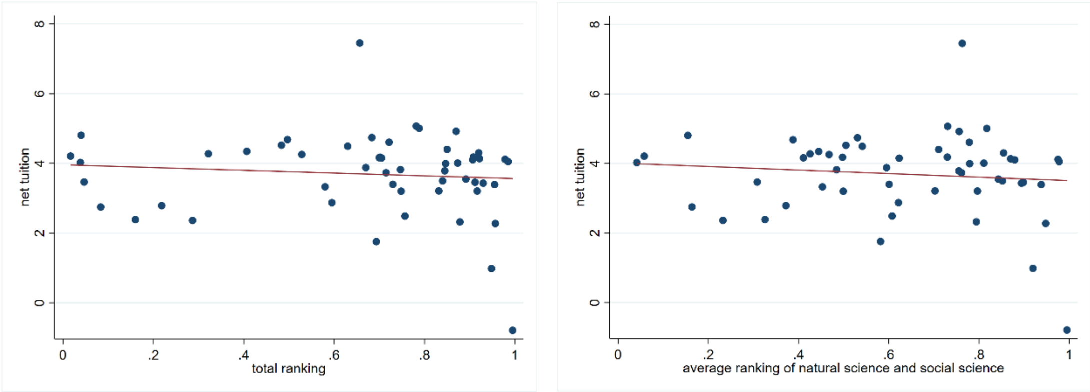
Note: Data source is Administrative Data on College Admissions in 2003. The middle of the box is the mean value of human capital in each province. The upper hinge of the box is 75th percentile and the lower hinge is 25th percentile. The lower adjacent value is $\mu - 3\sigma$ and upper adjacent value is $\mu + 3\sigma$, where μ and σ are the mean and standard deviation respectively.

Figure A3. Correlation between Average HC and Average Cognitive Ability (by Province)



Note: Data sources are 2003 administrative data and CFPS data. The value of average pre-college human capital is scaled to 0 to 1, and the cognitive ability test score is standardized to z-score. The correlation coefficient between them is 0.548, significant at 1% level.

Figure A4. Correlation between Net Tuition and College Qualities

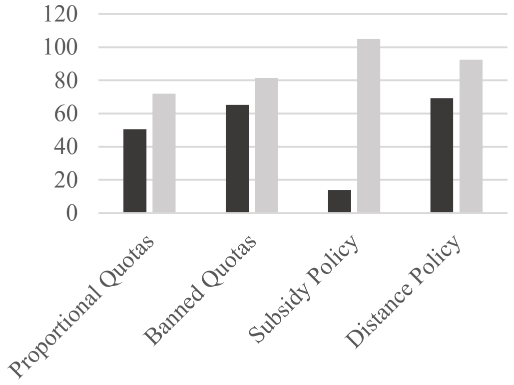


Panel A Panel B

Note: The data comes from 2013 CCSS data. X-axis of Panel A is the overall ranking of college quality, and the correlation coefficient between net tuition and college's ranking is -0.095. X-axis of Panel B is the average of college rankings in the natural and social sciences, and the correlation coefficient between net tuition and college's ranking is -0.087. There is no statistically significant correlation between net tuition and various quality measures.

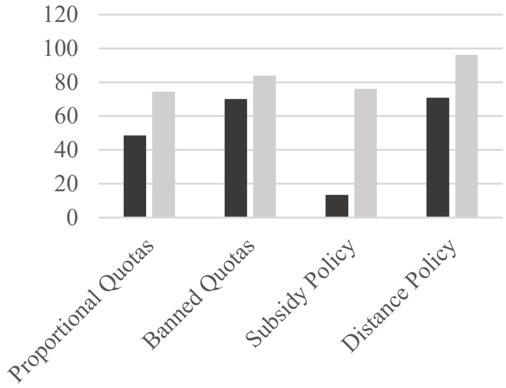
Figure A5. Average SES Characteristics of Better-off and Worse-off Students

Panel A Family Income (1,000 yuan)



(a) Matched by score percentile

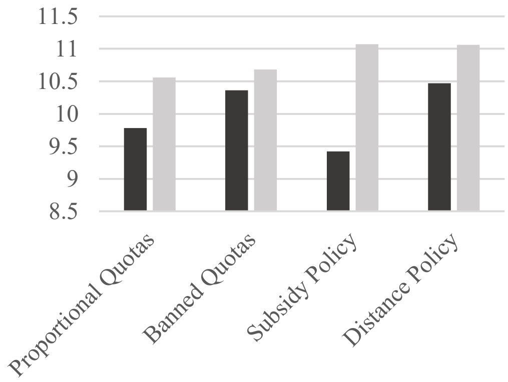
ΔU>0 ΔU<0



(b) Matched by human capital

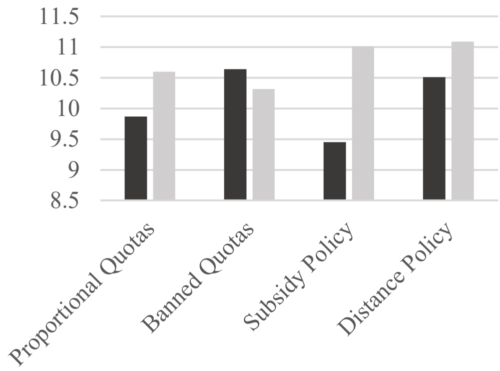
ΔU>0 ΔU<0

Panel B Parental Education (years)



(a) Matchedy by score percentile

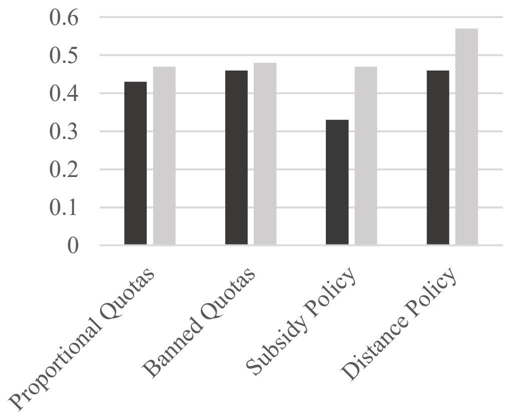
ΔU>0 ΔU<0



(b) Matched by human capital

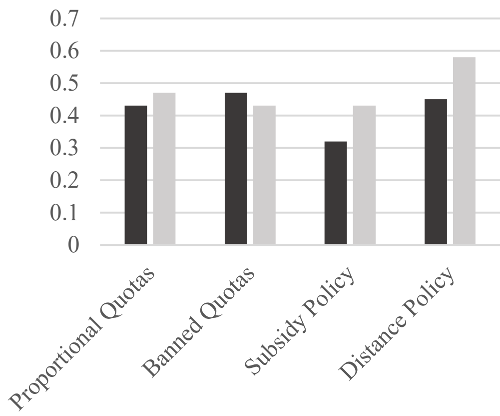
ΔU>0 ΔU<0

Panel C Ratio of Urban Hukou



(a) Matched by score percentile

ΔU>0 ΔU<0



(b) Matched by human capital

ΔU>0 ΔU<0

Table A1. An Overview of China's College Admissions System

	2009 (sampled year)	2022
	(1)	(2)
Number of students taking the *gaokao*	10.2 millions	11.9 millions
Number of four-year colleges	1,090	1,239
Number of Project 985 colleges	39	39
Number of Project 211 colleges (including 985)	116	116
Admission rates of four-year colleges	30.46%	39.22%
Admission rates of Project 985 colleges	1.69%	1.62%
Admission rates of Project 211 colleges	5.07%	5.01%

Note: The data is collected from the internet https://www.gov.cn/. Four-year colleges include Project 985 and 211 colleges.

Table A2. Geographical Distribution of High-quality Colleges

Region	Number of 985 colleges	% of 985 colleges	Number of 211 colleges	% of 211 colleges	% of high school graduates
	(1)	(2)	(3)	(4)	(5)
East	22	56.41%	63	54.31%	35.68%
Middle	6	15.38%	18	15.52%	33.14%
West	7	17.95%	24	20.69%	23.60%
Northeast	4	10.26%	11	9.48%	7.58%
Total	39	100%	116	100%	100%

Note: Data source is China Social Statistical Yearbook. The Data is for year 2009.

Table A3. Sample Selection

Data Processing	Number of students
Original data	10,679
Drop higher vocational colleges	9,075
Drop private undergraduate colleges	8,231
Retain humanity students and science students	7,634
Retain students took *gaokao* in 2009	6,631
Drop students whose exam provinces and exam scores are missing	6,371
Drop students whose gender and parents' income are missing	5,940
Drop students from Tibet	5,929

Note: CCSS2013 includes 65 higher education institutions, including seven higher vocational colleges, five private undergraduate colleges and 53 public undergraduate universities. Students are divided into two tracks: science and humanity, including some art and sport candidates. We don't include art and sport candidates in analysis. The students surveyed are all senior college students (the undergraduate program is a four-year program) and we only retain the students who took the exam and enrolled in college in 2009.

Table A4. Summary Statistics of Representative College Attributes (Obs = 500)

Variables	**Definition**	**Mean**	**Std**
Total rank	standardized overall ranking of Chinese colleges	0.501	0.289
Sci rank	standardized natural science ranking of college	0.501	0.289
Soc rank	standardized social science ranking of college	0.501	0.289
College 985	985 college = 1, others = 0	0.078	0.268
College 211	211 college (including 985) = 1, others = 0	0.232	0.423
Median tuition	median tuition fees of each college (1k RMB)	5.150	1.705
Ln(GDP)	2003 ln(GDP) of the city where the college is located	7.925	0.984
West	whether the college is in western region	0.178	0.383
Middle	whether the college is in middle region	0.320	0.467
East	whether the college is in eastern region	0.502	0.500

Note: The 500 colleges are four-year colleges included in Wu (2009). The overall ranking, natural science and social science ranking of colleges come from Wu (2009). The data of median tuition comes from Qiu and Zhao (2010) and the Internet. The GDP data comes from the 2003 statistical yearbooks of each province.

Table A5. Ability and Attended College Quality by Demographic Group

	Family Income			Parental Education			Hukou		
	low	high	Δ	low	high	Δ	rural	urban	Δ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
College Quality	0.671	0.709	-0.039***	0.676	0.701	-0.025***	0.667	0.714	-0.047***
			(0.008)			(0.008)			(0.008)
Score Percentile	0.741	0.753	-0.012**	0.747	0.748	-0.001	0.745	0.751	-0.006
			(0.006)			(0.006)			(0.006)
Human Capital	0.686	0.709	-0.023***	0.690	0.704	-0.014***	0.690	0.706	-0.016***
			(0.002)			(0.002)			(0.002)
N	2,888	2,573		2,440	2,821		2,892	2,420	

Note: Data source is CCSS 2013. Students groups are based on whether their family income is above the median (41,000 yuan per year), whether their parents' highest education years are above the median (12 years), and agricultural *hukou* vs nonagricultural *hukou*. College quality is measured by college rankings (normalized to 0 to 1) from Wu (2009). The asterisk represents the significance of the mean difference: * p<0.1, ** p<0.05, *** p<0.01.

Table A6. Relationship between Tuition, Subsidies and Student Characteristics

	Scholarship	Tuition waiver	Actual net tuition
	(1)	(2)	(3)
Score percentile	0.992***	0.289	-1.906*
	(0.297)	(0.207)	(1.053)
Ln(family income)	-0.050*	-0.151***	0.209***
	(0.023)	(0.016)	(0.028)
Parental education	0.015	-0.022***	0.007
	(0.011)	(0.007)	(0.015)
Male	-0.422***	-0.147***	0.549***
	(0.074)	(0.045)	(0.117)
Rural	0.115	0.433***	-0.529***
	(0.069)	(0.054)	(0.118)
College ranking	0.307	0.137	-0.568*
	(0.197)	(0.203)	(0.315)
Median tuition	-0.044	-0.078*	1.174***
	(0.060)	(0.041)	(0.101)
N	4381	5528	4381
R^2	0.030	0.086	0.177
Dep mean	0.956	0.642	3.627
Dep std	1.854	1.336	2.643

Note: Data source is CCSS 2013. Net tuition is equal to each college's median tuition minus the scholarship and tuition waiver. The units of the dependent variables are 1,000 yuan. Standard errors are shown in parentheses and calculated by clustering over colleges; * p<0.1, ** p<0.05, *** p<0.01.

Table A7. The Size of Student's Choice Set

Major	Group by Score Percentile	N	Mean score percentile	Choice set size
Science	Bottom Quintile	946	0.456	13.563
	Second Quintile	946	0.667	19.166
	Middle Quintile	943	0.815	28.582
	Fourth Quintile	947	0.915	36.891
	Top Quintile	941	0.978	45.677
Humanity	Bottom Quintile	243	0.349	10.918
	Second Quintile	240	0.567	11.425
	Middle Quintile	241	0.722	18.929
	Fourth Quintile	246	0.874	23.451
	Top Quintile	236	0.978	36.064

Note: Data source is CCSS 2013. Science students and humanity students are both divided into 5 equally-sized groups sorting by within-province score percentiles.

Table A8. Model Fit

College Characteristics	Science Track			Humanities Track		
		Actual	Predicted		Actual	Predicted
	N	Mean	Mean	N	Mean	Mean
Net tuition	4,723	3.52	3.59	1,206	3.46	3.42
Low income	1,641	3.27	3.33	352	3.22	3.25
Middle income	1,693	3.59	3.70	383	3.50	3.44
High income	1,389	3.75	3.77	471	3.71	3.61
Sci rank	4,723	0.72	0.72	1,206	0.57	0.57
Male	2,952	0.74	0.74	339	0.57	0.60
Female	1,771	0.67	0.68	867	0.57	0.56
Low income	1,641	0.71	0.71	352	0.59	0.58
Middle income	1,693	0.72	0.72	383	0.59	0.61
High income	1,389	0.72	0.72	471	0.52	0.52
Soc rank	4,723	0.66	0.66	1,206	0.69	0.69
Male	2,952	0.68	0.67	339	0.72	0.70
Female	1,771	0.64	0.65	867	0.68	0.69
Low income	1,641	0.65	0.65	352	0.66	0.66
Middle income	1,693	0.64	0.63	383	0.66	0.67
High income	1,389	0.70	0.71	471	0.78	0.77
Home province	4,723	0.59	0.59	1,206	0.64	0.64
Male	2,952	0.58	0.58	339	0.59	0.62
Female	1,771	0.62	0.61	867	0.66	0.65
College Distance	4,723	500.20	498.71	1,206	453.31	444.45
Male	2,952	514.38	505.94	339	534.01	467.27
Female	1,771	476.63	486.69	867	418.80	434.69
Low income	1,641	506.21	542.81	352	443.83	431.75
Middle income	1,693	503.17	499.79	383	486.86	486.61
High income	1,389	489.01	442.90	471	427.08	407.27
College 985	4,723	0.19	0.19	1,206	0.18	0.18
Low income	1,641	0.18	0.18	352	0.16	0.16
Middle income	1,693	0.20	0.18	383	0.21	0.19
High income	1,389	0.20	0.23	471	0.18	0.19

Note: The table shows the average characteristics of colleges that students from science or humanities track actually attending and predicted to attend. Data source is CCSS 2013.

Table A9. Robustness Check for Student Preference Estimations

	Baseline	New net tuition	Parallel mechanism	Weighted estimation 1	Weighted estimation 2
	(1)	(2)	(3)	(4)	(5)
Home province	3.201***	3.203***	3.345***	2.980***	3.311***
	(0.052)	(0.052)	(0.081)	(0.145)	(0.021)
Distance	-0.562***	-0.543***	-0.657***	-0.534***	-0.527***
	(0.055)	(0.055)	(0.085)	(0.130)	(0.022)
Distance×LowInc	-0.028	-0.042	0.045	-0.017	0.033
	(0.069)	(0.069)	(0.108)	(0.166)	(0.027)
Distance×HighInc	0.191***	0.151**	0.130	0.139	0.121***
	(0.069)	(0.069)	(0.111)	(0.168)	(0.028)
Sci rank	0.341*	0.427**	0.498	2.248***	0.110
	(0.189)	(0.224)	(0.353)	(0.755)	(0.108)
Sci rank×science	2.600***	2.242***	3.104***	2.840***	3.251***
	(0.152)	(0.159)	(0.249)	(0.486)	(0.082)
Soc rank	1.594***	1.677***	5.468***	3.889***	3.202***
	(0.230)	(0.263)	(0.550)	(1.014)	(0.130)
Soc rank×science	-1.025***	-1.027***	-3.406***	-1.739**	-2.496***
	(0.211)	(0.220)	(0.470)	(0.871)	(0.110)
Net tuition	-0.129***	-0.134***	-0.163***	-0.212***	-0.066***
	(0.018)	(0.017)	(0.027)	(0.041)	(0.008)
Net tuition×LowInc	-0.065***	-0.060**	-0.072*	-0.066	-0.104***
	(0.024)	(0.023)	(0.037)	(0.057)	(0.009)
Net tuition×HighInc	0.068**	0.067**	0.139***	0.031	0.077***
	(0.027)	(0.026)	(0.045)	(0.064)	(0.012)
ln(GDP)	0.232***	0.228***	0.275***	-0.101	0.214***
	(0.028)	(0.028)	(0.044)	(0.073)	(0.014)
Middle	-0.364***	-0.352***	-0.251***	-1.241***	-0.703***
	(0.062)	(0.062)	(0.095)	(0.185)	(0.024)
East	0.266***	0.278***	0.410***	0.089	-0.387***
	(0.057)	(0.058)	(0.090)	(0.130)	(0.021)
College type	control	control	control	control	control
N	160,070	160,070	71,408	160,070	160,070

Note: Data source is CCSS 2013. Column (1) is the baseline result. Column (2) is the result of changing net tuition variable. Column (3) is the result of the subsample of 15 provinces that use parallel (DA-like) mechanism. Column (4) and (5) are the estimation results after adjusting the sampling bias but adopt different weights. Standard errors are in parentheses, * p<0.1, ** p<0.05, *** p<0.01.

Table A10. Characteristics of Simulated Students

Variable	Obs	Mean	Std
Parental income (1,000 yuan)	62,140	61.209	211.103
Parental education years	62,140	10.131	3.332
Male	62,140	0.630	0.483
Rural	62,140	0.556	0.497
Score percentile	62,140	0.497	0.283
Science	62,140	0.667	0.471

Note: This table reports the characteristics of the generated college applicants sample for the use of counterfactual analysis, which is a representative sample of all "potential" college applicants, not just those admitted to colleges. See Section 7.1 and Appendix G.1.

Table A11. Matching Inequality under Partially Integrated Market

Scenario	**Score Percentile**		**Human Capital**	
	# of BPs	Degree of mismatch	# of BPs	Degree of mismatch
	(1)	(2)	(3)	(4)
(1) Benchmark	73.47	37.94	171.59	59.55
(2) No provincial quota with heterogeneous preferences	18.51	23.87	17.61	24.28
Partially integrated market				
(3) 20% integrated market	48.36	25.86	42.85	26.99
(4) 40% integrated market	40.90	25.62	40.91	26.16
(5) 60% integrated market	29.22	24.32	28.02	24.95
(6) 80% integrated market	22.59	23.97	22.90	24.44

Note: Data source is the generated college applicants sample and generated college sample described in Section 7.1 and Appendix G. The total number of students is 62,140, and the total number of colleges is 500. Matching inequality is measured by the number of blocking pairs (BPs) and the degree of mismatch, in which student ability is measured by within-province score percentile or constructed human capital.

Table A12. Matching Inequality by Demographic Group

(Degree of Mismatch per capita)

Scenario	Family income		Parent education		*hukou*	
	Low	High	Low	High	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A Within-province Score Percentile						
Benchmark						
(1) Current quotas with heterogeneous preferences	-2.11	2.11	-1.13	1.13	-0.58	0.77
Change Quota System						
(2) Proportional quotas with heterogeneous preferences	-1.72	1.72	-0.39	0.39	-0.12	0.16
(3) 20% integrated market with heterogeneous preferences	-1.11	1.11	-0.32	0.32	-1.49	1.95
(4) No provincial quota with heterogeneous preferences	-0.74	0.74	-0.48	0.48	-0.97	1.28
Change Heterogeneous Preferences						
(5) Current quotas with subsidy policy	-0.35	0.35	-0.58	0.58	-0.15	0.20
(6) Current quotas with distance policy	-1.07	1.07	-0.61	0.61	0.00	0.00
Panel B Human Capital						
Benchmark						
(7) Current quotas with heterogeneous preferences	3.97	-3.97	1.19	-1.19	0.27	-0.36
Change Quota System						
(8) Proportional quotas with heterogeneous preferences	4.84	-4.84	1.49	-1.49	0.41	-0.55
(9) 20% integrated market with heterogeneous preferences	1.24	-1.24	0.07	-0.07	-0.20	0.27
(10) No provincial quota with heterogeneous preferences	0.06	-0.06	0.11	-0.11	-0.38	0.50
Change Heterogeneous Preferences						
(11) Current quotas with subsidy policy	5.70	-5.70	1.73	-1.73	0.48	-0.64
(12) Current quotas with distance policy	4.98	-4.98	0.81	-0.81	0.07	-0.09

Note: Data source is the generated college applicants sample and generated college sample described in Section 7.1 and Appendix G. The total number of students is 62,140, and the total number of colleges is 500.

Table A13 Determinants of Student Attended College Quality under Counterfactual Policies

	Dependent variable: College quality ranking									
	Score Percentile					**Human Capital**				
	Benchmark	Proportional quotas	No Provincial quota	Subsidy Policy	Distance Policy	Benchmark	Proportional quotas	No Provincial quota	Subsidy Policy	Distance Policy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Score percentile	0.471***	0.766***	0.725***	0.473***	0.487***					
	(0.027)	(0.015)	(0.036)	(0.028)	(0.028)					
Human capital						0.665***	0.962***	0.655***	0.669***	0.677***
						(0.076)	(0.094)	(0.056)	(0.077)	(0.078)
Ln(income)	0.014	0.074***	-0.005	-0.031	-0.000	0.031**	0.066***	0.002	-0.027	0.004
	(0.012)	(0.009)	(0.007)	(0.019)	(0.000)	(0.015)	(0.010)	(0.009)	(0.017)	(0.018)
Parental edu	0.017	0.004	-0.009	0.015	0.009	0.001	0.001	0.001	0.000	0.011
	(0.013)	(0.007)	(0.006)	(0.011)	(0.012)	(0.014)	(0.008)	(0.013)	(0.000)	(0.011)
Male	0.014	-0.014***	-0.002	0.016*	0.005	0.008	-0.003	0.014**	0.006	0.002
	(0.009)	(0.005)	(0.004)	(0.009)	(0.011)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Rural	0.009	-0.003	-0.012*	0.000	0.013	0.021**	0.016*	0.004	0.013	0.012
	(0.009)	(0.008)	(0.006)	(0.000)	(0.009)	(0.009)	(0.009)	(0.011)	(0.010)	(0.011)
Province-track FE	√	√	√	√	√	√	√	√	√	√
Joint significance of socioeconomic var. (p-value)	0.403	0.000	0.180	0.173	0.700	0.081	0.000	0.128	0.322	0.761
N	18,089	18,089	18,089	18,089	18,089	18,089	18,089	18,089	18,089	18,089
R^2	0.236	0.566	0.599	0.242	0.248	0.251	0.371	0.486	0.252	0.259

Note: Data source is the generated college applicants sample and generated college sample described in Section 7.1 and Appendix G. The total number of admitted students is 18,089, and the total number of colleges is 500. The dependent variable is the college quality rankings from Wu (2009).

Table A14. Decomposition of Welfare Changes

Counterfactual Policies	**Score Percentile**			**Human Capital**		
	Change in average welfare (1k yuan)	Allocation effect (1k yuan)	Price effect (1k yuan)	Change in average welfare (1k yuan)	Allocation effect (1k yuan)	Price effect (1k yuan)
	$CS_{cf} - CS_f$	$CS_{cf} - CS_1$	$CS_1 - CS_f$	$CS_{cf} - CS_f$	$CS_{cf} - CS_1$	$CS_1 - CS_f$
	(1)	(2)	(3)	(4)	(5)	(6)
Subsidy Policy	0.972	0.015	0.958	0.954	0.021	0.933
Distance Policy	0.681	0.003	0.678	0.680	0.005	0.675

Note: Data source is the generated college applicants sample and generated college sample described in Section 7.1 and Appendix G. The total number of students is 62,140, and the total number of colleges is 500. Welfare change is measured by the change in the utility under each counterfactual policy relative to the actual matching outcome, transformed into monetary values through dividing by the tuition coefficient in the demand estimation.

Table A15. Wage Predictions

Dependent variable：Ln(wage)	Ability=Score Percentile		Ability=Human Capital	
	Science	Humanity	Science	Humanity
	(1)	(2)	(3)	(4)
College quality	-0.132	-0.332	0.257**	0.141
	(0.165)	(0.711)	(0.126)	(0.418)
Ability	0.084	-0.551	0.164***	0.145*
	(0.284)	(0.485)	(0.053)	(0.082)
College quality* Ability	0.199	0.580	-0.032	-0.005
	(0.173)	(0.745)	(0.020)	(0.060)
Home province	-0.039	-0.102**	-0.040	-0.101**
	(0.027)	(0.045)	(0.025)	(0.042)
Ln(family income)	0.037***	0.041**	0.030***	0.033
	(0.006)	(0.019)	(0.006)	(0.020)
Parental education	0.008**	0.030***	0.007*	0.025**
	(0.004)	(0.010)	(0.004)	(0.009)
Male	0.065***	0.080*	0.072***	0.085*
	(0.023)	(0.046)	(0.021)	(0.049)
Rural	-0.006	0.039	0.008	0.051
	(0.025)	(0.052)	(0.021)	(0.052)
Constant	7.615***	7.736***	6.603***	6.390***
	(0.264)	(0.426)	(0.320)	(0.535)
N	2117	520	2117	520
R^2	0.072	0.141	0.092	0.161
Dep Mean	8.005	7.892	8.005	7.892
Dep Std	0.401	0.479	0.401	0.479

Note: Data source is CCSS 2013. Standard error in parentheses. Students are divided by their major: science and humanity. College quality is measured by college quality rankings from Wu (2009). Columns (1) and (2) measure student abilities using score percentile, while Columns (3) and (4) measure student abilities using pre-college human capital. The regression includes an interaction term between college quality and student abilities. * p<0.1, ** p<0.05, *** p<0.01.

Online Appendix

Appendix A. Linear Transformation and Standardization of Raw *Gaokao* Scores

To assess students' ability across provinces, we standardize the raw *gaokao* scores into within-province-and-track percentile. Due to the lack of score data for *all* students in the 2009 *gaokao*, we use Administrative Data on College Admissions in 2003 to standardize scores. The standardization of scores includes two steps.

First, we convert the 2009 raw scores into equivalent 2003 raw scores through Equation (A1). We assume that the 2003 score is a linear transformation of the 2009 score, and the scores of different province-major track have different transformation coefficients:

$$\mathrm{S}_{03pt} = a_{pt} * \mathrm{S}_{09pt} + b_{pt}. \tag{A1}$$

Where S_{03pt} and S_{09pt} are random variables representing the scores of students in province p and track t in 2003 and 2009, respectively. Within the same province-track, the mean and variance of the distributions of S_{03pt} and S_{09pt} will vary depending on the different test questions in the two years.[1] S_{03pt} is collected from students admitted to the 53 colleges in Administrative Data on College Admissions in 2003, while S_{09pt} is collected from students admitted to the 53 colleges in 2013 CCSS data.

We observe $\mathrm{E}(\mathrm{S}_{pt})$ and $\mathrm{Var}(\mathrm{S}_{pt})$ in both years from the data. Through Equations (A2)-(A3), we calculate out linear transformation coefficients a_{pt} and b_{pt} for each province-major track.

$$\mathrm{E}(\mathrm{S}_{03pt}) = a_{pt} * \mathrm{E}(\mathrm{S}_{09pt}) + b_{pt}. \tag{A2}$$

$$\mathrm{Var}(\mathrm{S}_{03pt}) = a_{pt}^2 * \mathrm{Var}(\mathrm{S}_{09pt}). \tag{A3}$$

Through the transformation coefficients, we get the equivalent value of a certain realization of S_{09pt} in 2003. This linear transformation does not change the relative ranking of students' test performance. Students at the top of their 2009 scores were still at the top of their 2003 equivalent scores.

Second, we standardize the raw scores into within-province-and-track percentiles.

$$percentile_{pti} = 1 - \frac{\sum_{n=1}^{N_{pt}} 1\{s_{ptn} \geq s_{pti}\}}{N_{pt}} \tag{A4}$$

Where s_{ptn} is the raw score of all other students in the same province-track as student i, while

[1] We do not assume the distribution of random variables S_{03pt} and S_{09pt}. For ease of understanding, readers can regard them as a normal distribution.

N_{pt} is the total number of students in province p and track t. Through Equation (A4), we obtain standardized test scores that are comparable across provinces. The higher the raw score, the higher the within-province ranking value for students.

Appendix B. Measurement Model of the Latent Pre-College Human Capital

We assume that the *gaokao* scores, NCEE, and college GPAs are both noisy measures of latent human capital (ability), θ^0. Latent factor model contains the following two measurement error equations:

$$\text{NCEE}_p = \kappa_{1,p} + \lambda_{1,p}\theta^0 + \sigma_{1,p}\nu_1, \tag{A5}$$

$$\text{GPA}_s = \kappa_{2,s} + \lambda_{2,s}\theta^0 + \sigma_{2,s}\nu_2, \tag{A6}$$

where NCEE_p is the 2009 original *gaokao* scores of students from province p, standardized to a range of 0-1. The parameters $\kappa_{1,p}, \lambda_{1,p}$ and $\sigma_{1,p}$ are subscripted by p to allow for the province-specific exam papers. GPA_s is the four-year average GPAs of students in college s, standardized to a range of 0-4. The parameters $\kappa_{2,s}, \lambda_{2,s}$ and $\sigma_{2,s}$ are subscripted by s to allow for college-specific inputs in both human capital production and GPA measurement technology. ν_1 is the measurement error, while ν_2 includes both measurement error and random shocks in the human capital production function during college education. We assume that both ν_1 and ν_2 follow a standard normal distribution, are independent across provinces and colleges, i.i.d. across individuals, mutually independent, and are independent of θ^0.

We estimate the model using the CCSS data, which contains information on *gaokao* scores and college GPA. We assume that θ^0 of students in each province follows a normal distribution, $\theta^0 \sim N(\mu_p^\theta,\ (\sigma_p^\theta)^2)$. Under independence assumptions about the error terms, we identify parameters $\{\kappa, \lambda, \sigma\}$ through the conditional mean, conditional variance, and conditional covariance of *gaokao* scores and college GPA.

Following the standard approach in factor model analysis, we normalize $\kappa_{1,p^*} = 0$ and $\lambda_{1,p^*} = 1$ for a specific p^* to pin down the position and scale of the latent human capital θ^0. We assume that the conditional distribution of measurement errors v_1 and v_2 is equal to the unconditional distribution:

$$E(v_1|p, s, \theta^0) = E(v_1) = 0$$

$$E(v_2|p, s, \theta^0) = E(v_2) = 0$$

$$Var(v_1|p, s, \theta^0) = Var(v_1) = 1$$

$$Var(v_2|p, s, \theta^0) = Var(v_2) = 1$$

Based on above assumptions, we identify parameters $\{\kappa, \lambda, \sigma\}$ through the conditional mean, conditional variance, and conditional covariance of *gaokao* scores and college GPA:

$$\text{E}(\text{NCEE}_p|s) = \kappa_{1,p} + \lambda_{1,p}E(\theta^0|p, s)$$

$$\mathrm{E}(\mathrm{GPA}_s|p) = \kappa_{2,s} + \lambda_{2,s}E(\theta^0|p,s)$$

$$\mathrm{Var}(\mathrm{NCEE}_p|s) = {\lambda_{1,p}}^2\mathrm{Var}(\theta^0|p,s) + {\sigma_{1,p}}^2$$

$$\mathrm{Var}(\mathrm{GPA}_s|p) = {\lambda_{2,s}}^2\mathrm{Var}(\theta^0|p,s) + {\sigma_{2,s}}^2$$

$$\mathrm{Cov}\left(\mathrm{NCEE}_p, \mathrm{GPA}_s\right) = \lambda_{1,p}\lambda_{2,s}\mathrm{Var}(\theta^0|p,s)$$

Cancelling out $E(\theta^0|p,s)$ and $\mathrm{Var}(\theta^0|p,s)$ gives three moment conditions for each combination of p and s:

$$\mathrm{E}(\mathrm{NCEE}_p|s) = \kappa_{1,p} + \frac{\lambda_{1,p}}{\lambda_{2,s}}\left(\mathrm{E}(\mathrm{GPA}_s|p) - \kappa_{2,s}\right). \tag{A7}$$

$$\mathrm{Var}(\mathrm{NCEE}_p|s) = \frac{\lambda_{1,p}}{\lambda_{2,s}}\mathrm{Cov}\left(\mathrm{NCEE}_p, \mathrm{GPA}_s\right) + {\sigma_{1,p}}^2. \tag{A8}$$

$$\mathrm{Var}(\mathrm{GPA}_s|p) = \frac{\lambda_{2,s}}{\lambda_{1,p}}\mathrm{Cov}\left(\mathrm{NCEE}_p, \mathrm{GPA}_s\right) + {\sigma_{2,s}}^2. \tag{A9}$$

The identification requires: (1) data are from at least two different provinces and two different colleges, (2) students from each province attend both colleges. These data will generate four combinations of p-s and in total 4*3=12 moments. Under the normalization where $\kappa_{1,p^*} = 0$ and $\lambda_{1,p^*} = 1$ for a specific p^*, the number of measurement parameters is 10, so they can be identified. The model is over-identified and we use GMM to estimate the parameters.

After identifying the parameters $\kappa_{1,p}, \lambda_{1,p}$ and $\sigma_{1,p}$ in Equation (A5), we can recover the provincial distribution of θ^0:

$$E_p(\theta^0) = \frac{E_p\left(NCEE_p\right) - \kappa_{1,p}}{\lambda_{1,p}}. \tag{A10}$$

$$Var_p(\theta^0) = \frac{Var_p\left(NCEE_p\right) - \sigma_{1,p}^2}{\lambda_{1,p}^2}. \tag{A11}$$

Appendix C. Calculating Blocking Pairs

Step 1: Construct the set of feasible colleges of each student i. The feasible set of i include colleges whose cutoff score is lower than the *gaokao* score of student i. The definition of feasible set A_i is shown as following:

$$A_i = \left\{ j \in J: s_i > \min_{\varphi(k)=j} s_k \right\},$$

where φ is a realized matching between students and colleges. The cutoff score of college j is the minimum *cross-provincially comparable ability* (within-province-and-track percentile or human capital) of all the students it admitted, which is $\min_{\varphi(k)=j} s_k$. If i's standardized score is above j's cutoff, i.e. $s_i > \min_{\varphi(k)=j} s_k$, then j is feasible for i and belongs to A_i.

Step 2: Compare the quality q_j of each $j \in A_i$ to $q_{\varphi(i)}$. The rank ordering of colleges is shown in Equations (A16) -(A17) (in Appendix G). If the quality of the feasible college j is higher than that of i's matched college $\varphi(i)$, $q_j > q_{\varphi(i)}$, then (i,j) forms a blocking pair, and the dummy variable $1\{q_j > q_{\varphi(i)}\}1\{s_i > \min_{\varphi(k)=j} s_k\}$ equals to 1.

Step 3: The total number of blocking pairs in allocation φ, $B(\varphi)$, is the sum of all students' above-mentioned dummy variables. The number of blocking pairs for each student, $B_i(\varphi)$, is the sum of above-mentioned dummy variables involving student i:

$$B(\varphi) = \sum_i \sum_j 1\{q_j > q_{\varphi(i)}\} 1\{s_i > \min_{\varphi(k)=j} s_k\}.$$

$$B_i(\varphi) = \sum_j 1\{q_j > q_{\varphi(i)}\} 1\{s_i > \min_{\varphi(k)=j} s_k\}.$$

Appendix D. Deferred Acceptance with Partially Integrated Market (DA-PIM)

The *DA-PIM Algorithm* is the following:

Stage 1. Form a student applicant queue with a descending order of their inter-provincial score rankings, using tie-breaking rule if necessary. Each student is attached with a complete preference order list over colleges.

Stage 2. Start with the first (remained) student in the applicant queue. Consider the first college in his (remained) preference order list. The student is removed from the applicant queue.

(i) If the college has not yet used up the guaranteed quota of the student's corresponding province, then admit the student by using the guaranteed quota.

Upon admitting the student, if the capacity of the college has been exceeded, the college rejects the inter-provincially lowest score-ranked student admitted by using flexible quota. (There must be such a student). The student who is rejected by the college is sent back to the top of the student applicant queue, with the college rejecting him removed from his preference order list. Go back to Stage 2.

(ii) If the college has used up the guaranteed quota of the student's corresponding province, the student will be compared with those being admitted by the guaranteed quota, and the one with the lowest score ranking will be rejected by the guaranteed quota. If the college does not use up its capacity, the student being rejected by the guaranteed quota will be admitted by flexible quota.

However, if the college has already used up its capacity, the student will be compared to other students admitted by flexible quota, and the inter-provincially lowest score-ranked student will be rejected by the college. He then will be sent back to the top of the applicant queue, with the college removed from his preference order list. Go back to Stage 2.

The algorithm ends when the applicant queue is empty. The admission, including the admitted college and the admitted quota type (guaranteed or flexible) of each student, is finalized.

D.1 Stable Outcome Respecting Provincial (Guaranteed) Quota

Definition. A matching outcome is *stable while respecting provincial quota*, if there does not exist a student who prefer to his matched college (including unmatched) a college which: (i) has unused guaranteed quota of the province from which the student come; or has fulfilled its guaranteed quota of this province but admit students from the same province with lower score rankings, or (ii) has unused capacity, or (iii) has fulfilled its capacity, but admit students with inter-provincially lower score rankings by using its flexible quota.

***Theorem.* Under the DA-PIM algorithm: (i) the matching outcome is stable while respecting provincial quota. (ii) the matching outcome is student-optimal among all the stable matching**

outcomes while respecting provincial quota, given the tie-break rule. (iii) Students will report their preference order truthfully.

We prove this theorem in the following.

D.2 the Extended Matching Problem and the Extended DA-PIM

Consider the following *extended matching problem*. First, denote (j, p) as the provincial *p* division of college *j*. College-division (j, p) has the quota equal to the guaranteed quota of college *j* for province *p*. Its priority order for students is the following: it puts all students from province *p* above students from other provinces; among students from province *p*, it orders them according to their score rankings; among students from other provinces, it orders them according to their inter-provincial score rankings. In addition, college *j* has a flexible division, denoted as (j, f). The quota of (j, f) is the college capacity minus the sum of guaranteed provincial quotas. Its priority order for students is purely based on their inter-provincial score rankings. Note that each college-division has a fixed quota.

Now consider the student preference for each college division: First, we preserve student preference order for each college. That is, if a student prefers college *j* to college *j'*, then he prefers every division of college *j* to every division of college *j'*. Second, within a college, the student preference order is the following: he prefers the local division (i.e., division of his local province) most, and prefers the flexible division second. For other provincial divisions, preference order is predetermined (e.g., according to an alphabetic order) and the same among all students.

The extended DA-PIM algorithm is DA imposing on extended matching problem, with the only exception that students are only allowed to propose one by one, as under the (original) DA-PIM. It proceeds as the following:

Stage 1. Form a student applicant queue with a descending order by their inter-provincial score rankings, using tie-breaking rule if necessary. Each student is attached with a preference order list of college-divisions, according to the extended matching problem.

Stage 2. Start with the first (remained) student in the applicant queue. Consider the first college-division in his (remained) preference order list. Remove the student from the applicant queue.

(i) If the college-division has not yet used up its quota, admit the student. Remove the college-division from the preference list of the student. Go back to Stage 2.

(ii) If the college-division has used up its quota, the student will be compared with those being admitted, and the one with the lowest priority according to the extended matching problem is rejected. The student rejected is sent back to the top of the applicant queue. The college-division is removed from preference order list of either the admitted or rejected student. Go back to Stage 2.

The algorithm ends when the applicant queue is empty. The admitted then is finalized.

We define the matching outcome of the original DA-PIM and of the extended DA-PIM is the same, if: (i) a student matched to the guaranteed quota of a college under the DA-PIM is matched to the local-division of the same college under the extended DA-PIM. (ii) A student matched to the flexible quota of a college under the DA-PIM is matched to a nonlocal-division (including purely flexible division) of the same college under the extended DA-PIM. (iii) A student rejected by a college under the DA-PIM is also be rejected by all the divisions of the same college.

Lemma 1. **The matching outcome of the extended DA-PIM algorithm is equal to the matching outcome of the (original) DA-PIM.**

Proof. Under original DA-PIM, an application (i.e., a particular college of a student) drawn from the applicant queue ends (i.e., before we start next draw from the applicant queue) with two possible results: either the application is accepted by the guaranteed quota or flexible quota of the college, with or without another student being rejected, or the applicant itself is rejected be both the guaranteed quota and flexible quota of the college.

A proper adjustment for what forms an "application" is needed under the extended DA-PIM, where an applicant originally consists only a college-division of a student, not the whole college. Note that when a student is being rejected by a particular college-division, he is immediately considered by the next division of the same college in his preference list, until exhausting all the divisions of the college. So successive "applications" (if any) within a college of the same student can be aggregated and defined as an application, just like the application under the original DA-PIM.

That is, an application for either algorithm, is defined as starting from a particular college of a student being considered, ending as one of three: (i) the student is admitted by the college (guaranteed or flexible quota, i.e., local- or other-division), without rejecting another student, (ii) the student is admitted, rejecting another student, (iii) the student himself is rejected by the college.

Our proof proceeds by induction. For the very first student with its first-choice college, i.e., the first application, the matching outcome is obviously the same for either the original or extended DA-PIM.

Suppose until k applications, the matching outcome is the same: the same group of students are admitted by the same type (or division) of quotas of the same colleges, and the rejected student at the end of each application (if any) is the same.

Consider the k+1 application, which (by assumption) applies the same college by the same student under the two algorithms. We argue that for any result this application counter with under the original DA-PIM, the same result he will have under the extended DA-PIM.

Case 1 (under original DA-PIM). The application is accepted by the guaranteed quota of the college, without rejection of any student, i.e., the college has unused guaranteed quota.

Then under extended DA-PIM, by induction assumption, there must be unused guaranteed (i.e., local-division) quota of the college. Denote the proposer is student i. With a bit abuse of notation, denote the local division of student i is (j, p). It is obvious that student i must also be admitted by division- (j, p) (i.e., guaranteed quota) of the college.

Suppose now the college exceeds its capacity (under original DA-PIM). Then, under the extended DA-PIM, before the applied student is accepted, all the divisions of the college are fulfilled. Then there is one student, student i', is (tentatively) admitted by division- (j, p) as her *nonlocal*-division and has the lowest score ranking among all non-local students admitted by division- (j, p).

Since student i', as a non-local student, is tentatively admitted by a division-(j, p) before application k+1, it has been rejected by all the divisions with a predetermined higher order than division- (j, p), as well as its local division (denoted as division- (j, p')). Therefore, student i''s local division must be fulfilled by local students, and all the nonlocal students admitted by divisions with a higher predetermined order than division- (j, p), except division- (j, p'), must have a higher inter-provincial score ranking that student i'.

So, after student i is accept, student i', rejected by division- (j, p), must be considered by other division with a lower predetermined order than (j, p), except division- (j, p'). Then, after a (college-division) rejection-and-admission chain, the non-local student finally rejected by the college is the one with the lowest inter-provincial score ranking in all the divisions with predetermined order lower than or equal to (j, p), except (j, p'). Note that student i' is the student with the lowest score rankings among all nonlocal students in all the divisions with predetermined order higher than (j, p), except (j, p'). Note also that division- (j, p') is fulfilled by local students. Then, finally, the student being rejected by the college is the single non-local student with the lowest inter-provincial score-ranking among *all* divisions (including (j, p')). The matching result is exactly the same as under the original DA-PIM.

Case 2 (under original DA-PIM). The application has to compete with other students accepted by the guaranteed quota of the college, i.e., the college has fulfilled its guaranteed quota.

Denote the proposer as student i, and the local division of student i is division- (j, p). Under the original DA-PIM, the student with the lowest score ranking among students being admitted by the guaranteed quota, denoted as student i', must be rejected from guaranteed quota ($i=i'$ is possible). If the college has not exceeded its capacity, student i' is admitted by flexible quota; if exceed, the student with the lowest inter-provincial score rankings among all the students using flexible quota is rejected.

Now consider the extended DA-PIM. Case 2 implies that under the extended DA-PIM, the division- (j, p) has fulfilled local students, and student i' will be rejected by division- (j, p).

If the college has not exceeded its capacity, then there must be at least one division (except division- (j, p)) has unused quota. Then student i' must be accepted by the college, and no students admitted by the college will be rejected, although the rejection of i' from division-A may trigger a rejection-and-admission chain *within* the college.

If the college has exceeded its capacity, then the rejection of student i' from division- (j, p) will trigger a rejection-and-admission chain, resulting in a non-local student with the lowest interprovincial score ranking across provinces being rejected.

As a whole, under Case 2, the matching result is the same as under the original DA-PIM. This ends the proof.

Note that the extended DA-PIM algorithm is not a classical DA, in which students propose simultaneously. We now proceed to prove their matching outcome is also the same.

***Lemma 2*. The matching outcome of the extended DA-PIM is the same as the classical DA based on college division, in which students propose simultaneously.**

Proof. In the following, for brevity, we call a college-division as a school. The matching problem is based on school. The extended DA-PIM is a mechanism where students propose according to a specific order, i.e., their score rankings. We can prove that for *any* order students propose, the DA algorithm achieves the same matching result, i.e., the student optimal stable matching. This is easy by noticing that the well-known theorem stating that the classical DA achieves the student optimal stable matching (e.g., Gale and Shapley, 1962; Roth and Sotomayor, 1990, Theorem 2.8 and 2.12) does not depend on the proposing order.

We first demonstrate that the matching results are stable under the DAs proposed by the students in *any* order. Suppose not, and there exists a blocking pair, student i and school j. That is, student i prefers school j to his current matching school (including being unmatched), and one of the two following scenarios happens:

Scenario 1: School j is not full. Then School j has never been fulfilled during the entire admission process. However, student i has proposed to j, before he submits to the currently matched school, and been admitted to school i. Then student i will never be rejected by school j, because school j always has unused quota. Contradiction to student A being admitted by other school or unmatched.

Scenario 2: school j admits a student with a lower priority than student i. Then throughout the admission process, school j is either not fulfilled, or is fulfilled but admits at least one student with lower priority than student i. Since student i has proposed to j, he will be admitted by A forever. Contradiction.

Next, we prove the stable matching outcome obtained by the DA proposed by students in *any* order is the student optimal stable matching outcome for students. We call a school is *achievable* to a student if the student is admitted by the school in some stable matching. We prove under the DA proposed by students in any order, no student is ever rejected by an achievable school.

The proof is by induction. Assume that up to a given step (i.e., a given draw from the applicant queue) in the procedure no student has yet been rejected by a school which is achievable for him. At this step, suppose school j rejects student i. Then school j must be fulfilled with students all having higher priority than student i.

Consider any of those students, e.g., student i'. Student i' prefers school j to any school except for those who have previously rejected him, and hence (by the inductive assumption) are unachievable for him. Consider a hypothetic matching μ that matches student i to school j and everyone else to an achievable school. Then student i' prefers school j to his matched school under μ. So the matching μ is unstable, since it is blocked by student i' and school j. Therefore, there is no stable matching that matches student i to school j, and so they are unachievable for each other, which completes the proof.

The main theorem can be proved based on Lemma 1 and 2. Before that, we note that, the classical original DA achieves student optimal stable matching and students are truth-telling. (Gale and Shapley, 1962; Roth and Sotomayor, 1990, Theorem 2.8, 2.12 and 4.7). This directly applies to our classical DA-PIM based on college-divisions, and by Lemma 2, to extended DA-PIM based on college-division.

Proof of the Theorem. According to Lemma 1 and 2, the matching outcome of the (original) DA-PIM is equal to the classical DA, where students propose simultaneously, and the matching is based on college-division. We proceed the proof by examining three claims one by one.

(i) The matching outcome is stable while respecting provincial quota.

We proceed by arguing that if there is a blocking pair under DA-PIM, there must be one under the extended DA-PIM (base on college-divisions). Since the extended DA-PIM is stable, the DA-PIM must be, and a contradiction is found.

Suppose there is a blocking pair in which a student i who prefer to his matched college (including unmatched) a college j. There are three possibilities:

(1) College j has unused guaranteed quota of the province from which the student come; or has fulfilled its guaranteed quota of this province but admit students from the same province with lower score rankings. In this case, the extended DA-PIM is unstable with a blocking pair between student i and student i's local division of college j.

(2) College j has unused capacity. In this case, there is at least one division in college j has unused quota. Student i and such a division of college j form a blocking pair.

(3) College j has fulfilled its capacity, but admit students with inter-provincially lower score rankings than student i by using its flexible quota. In this case, there is at least one division (of student i's nonlocal division or purely flexible division) in college j has admitted a nonlocal student with lower inter-provincial score ranking than student i. Student i and such a division of college j

form a blocking pair.

(ii) The matching outcome is student-optimal among all the stable matching outcomes while respecting provincial quota, given the tie-break rule.

Suppose not. There is another stable matching outcome respecting provincial quota (e.g., μ') under which one student (student i) is matched to college j', while he is matched to college j under the DA-PIM (denoted as μ). And student i prefers college j' to college j. (And no other students matched to a less preferred college under μ' than μ.)

We first argue that for μ', there is a corresponding matching outcome μ_e' based on college-division under the extended matching problem, which is consistent with μ' and stable.

We construct μ_e' as the following:

(1) All the students must be matched to the same type quotas in the same college as under the μ', including unmatched. In particular, if a student is matched to the guaranteed quota under μ', he must be matched to the local-division under μ_e'. If a student is matched to the flexible quota under μ', he must be matched to the nonlocal-division (including purely flexible division) under μ_e'.

(2) Within any colleges, the matching is constructed such that there does not exist a student matched to a nonlocal-division who prefers another non-local division, by the predetermined student preference order, to his matched division, and the division is not fulfilled or is fulfilled but admits a nonlocal student with lower inter-provincial score rankings. (This property can be realized by running a DA between students admitted by non-local divisions of this college and the remained quota of each division of the college after admission using its guaranteed quota, as indicated in (1)).

The construction of μ_e' insure that after step (1), there is no blocking pair between any quota type of any college and any student. Step (2) insures there is no block pairs between students and college-division within the any nonlocal divisions in the college.

By Lemma 1, there is an equivalent matching outcome, denoted as μ_e, under the extended DA-PIM corresponding to μ under DA-PIM. $\mu_e \neq \mu_e'$. Due to DA property, μ_e is a student optimal matching among all the stable matching under the extended matching problem, including μ_e'. However, under μ_e', student i is matched to a division of college j', which is preferred to a division of college j, to which he is matched under μ_e. This contradicts to the student optimal stability of the extended DA-PIM under μ_e.

(iii) Students will report their preference order truthfully.

Imagine that after students submit their preference order under DA-PIM, those orders are "translated" into the extended preference order lists as defined in our extended matching problem. Then the extended DA-PIM is used to match students to college-divisions. When the algorithm ends, we translated the matching outcome back to an outcome indicating only the matched pairs of college-quota-type and students. By Lemma 1, translations would not change the matching outcome of DA-PIM. Therefore, a truthful preference reporting under DA-PIM would be translated into a truthful preference reporting under the extended DA-PIM, which is a dominant strategy under the extended DA-PIM, due to its DA property. This implies that truthful reporting is a dominant strategy under the DA-PIM.

Appendix E. Estimating Net Tuition

This paper includes two net tuition variables. In Section 6.1, we include $NetTuition_{ij}$ into student's utility function. And in Appendix E, we would use a new net tuition measure $CfTuition_{ij}$ to check the robustness of the baseline estimation.

E.1 Estimating $\boldsymbol{NetTuition_{ij}}$

(1) We divide all students into 53 subsamples based on the college they actually attended.

(2) In each subsample, we estimate Equation (3), rewritten as Equation (A12) separately for the merit-based scholarship and need-based tuition waiver. The predicted coefficients of scholarship and tuition waiver are thus different among each college. It should be noted that the 53 group coefficients are different from the coefficients shown in Columns (1)-(2) of Table A6, which pool all colleges together.

$$y_{ij} = \delta_{0j} + \delta_{1j}Score_i + \delta_{2j}\, ln(\,income)_i + \delta_{3j}ParentEdu_i + \delta_{4j}Male_i + \delta_{5j}Rural_i + e_{ij}. \tag{A12}$$

(3) Based on the predicted coefficients, we can predict the amount of scholarships and tuition waiver that a student is expected to obtain after attending a college that he does not actually attend. Thus, the $\widehat{Scholarship_{ij}}$ and $\widehat{TuitionWaive_{ij}}$ for each student i and each college $j \in A_i$ are known. The $MedianTuition_j$ for each college is observable and calculated from public data. Based on Equation (5), rewritten here as (A13), we can obtain the counterfactual net tuition by subtracting the above two subsidies from the median tuition of each college.

$$\widehat{NetTuition_{ij}} = MedianTuition_j - \widehat{Scholarship_{ij}} - \widehat{TuitionWaive_{ij}}. \tag{A13}$$

E.2 Estimating $\boldsymbol{CfTuition_{ij}}$

(1) In CCSS 2013, we can observe the amount of a student's scholarships and tuition waiver received from the college she actually attended. According to Equation (A14), we can calculate out the actual net tuition of each student.

$$NetTuition_{ij} = MedianTuition_j - Scholarship_{ij} - TuitionWaive_{ij} \tag{A14}$$

(2) We divide all students into 53 subsamples based on the college they actually attended. In each subsample, we estimate Equation (A12) with dependent variable being the net tuition in Equation (A14). The predicted coefficients of net tuition are different among each college. It should be noted that the 53 group coefficients are different from the coefficients shown in Columns (3) of Table A6, which pool all colleges together.

(3) Based on the predicted coefficients, we can simulate the amount of net tuition that a student is expected to pay after attending a college that he does not actually attend. We name this new net tuition variable as $CfTuition_{ij}$, and replace $NetTuition_{ij}$ with it in Appendix F to re-estimate utility function.

Appendix F. Robustness Checks

We examine the robustness of the baseline estimation results in three ways: changing how net tuition is estimated, excluding observations corresponding to contexts with nonparallel preference submissions (i.e., non-DA mechanisms), and adjusting for sampling bias.

F.1 Changing Net Tuition Estimation

In our baseline specification, we estimate the net tuition of colleges not attended by students by subtracting the predicted scholarship and subsidy from the median tuition of the college. As a robustness check, we directly predict the net tuition separately for each college by regressing the observed student net tuition on student characteristics (as in Appendix E). Column (2) of Table A9 shows the preference estimation using the new net tuition measure. The values and statistical significance of each parameter are similar to benchmark estimation (in Table 4), which proves the robustness of our baseline results.

F.2 Correcting Estimation Bias Caused by the Matching Mechanism

Our estimation strategy relies on the stability assumption implied by the DA mechanism. Though many provinces adopted admissions algorithms similar to the DA mechanism (or parallel preference submissions) in 2009, some provinces use the non-DA/nonparallel matching method. In these provinces, the admission rules may induce students to manipulate their preferences at least more frequently, which may damage the stability of the matching results. We drop students who took the *gaokao* in these provinces from the sample and estimate the same model. Column (3) of Table A9 shows that the estimates are similar for most coefficients.

F.3 Adjusting for Sampling Bias

CCSS (2013) sampled 53 public colleges across the country and then surveyed a sample of students at each college. The sampling is choice-based, unlike the traditional direct sampling of decision-makers. To adjust for sampling bias, we modify the familiar exogenous sampling maximum likelihood estimator by weighting each observation's contribution to the log-likelihood (Manski & Lerman, 1977).

We use two weighting indexes. First, we calculate the weights based on the colleges' location and type (Wu & Zhong, 2020). Let G_{lt} denote the set of colleges that are of type t and are located in location l, where $l \in \{\text{east}, \text{middle}, \text{west}\}$ and $t \in \{985, 211, \text{Other}\}$. The probability weight imposed on college $j \in G_{lt}$ is the quotient of the probability that j is drawn from G_{lt} in the population and the probability that j is drawn from G_{lt} in our sample. Second, we calculate the weights using the number of college enrollments in the population and sample (Manski & Lerman, 1977). The weight imposed on college j is $Q(j)/H(j)$, where $Q(j)$ is the fraction of college entrants attending j in 2003 and $H(j)$ is the fraction of students surveyed in j in the sample. The weighted estimation results are shown in Column (4) and (5) of Table A9. The results are close to those in Table 4, which means that the sampling of our data is representative.

Appendix G. Constructing Representative Student and College Sample

G.1 Student Sample

Each student is characterized by their gender, *hukou* status (agricultural or urban), residential province, *gaokao* scores, family income, and parental education. We first divide students into four demographic groups based on the combination of gender and *hukou* status. Let k denote the demographic group, and p denote students' residential province and track. We then assume that students' scores, s, family income (in logarithmic scale), inc, and parents' years of education, edu, follow a joint normal distribution within each group in each province:[2]

$$(inc, edu, s)_{kp} \sim N\left(\begin{pmatrix} E_{kp}(inc) \\ E_{kp}(edu) \\ E_{kp}(s) \end{pmatrix}, \begin{pmatrix} Var_{kp}(inc) & Cov_{kp}(inc, edu) & Cov_{kp}(inc, s) \\ . & Var_{kp}(edu) & Cov_{kp}(edu, s) \\ . & . & Var_{kp}(s) \end{pmatrix}\right), \quad \text{(A15)}$$

where s represents either the *gaokao* score or the human capital θ_0 defined in Section 3.4. First, we estimate $E_{kp}(s)$ and $Var_{kp}(s)$ when s represents the *gaokao* score using the 2003 administrative data. We convert those two score statistics into the equivalent score statistics of 2009 according to the linear transformation shown in Appendix A. We then estimate $E_{kp}(s)$ and $Var_{kp}(s)$ when s represents the human capital (θ_0), using both the linear transformation of scores between 2003 and 2009 in Equation (A1), and the linear relationship between score and human capital shown in Equation (A5). Finally, we estimate $Cov_{kp}(inc, s)$ and $Cov_{kp}(edu, s)$ using purely the CCSS 2013 data and necessary transformation formulas.

We estimate $E_{kp}(inc)$, $E_{kp}(edu)$, $Var_{kp}(inc)$, $Var_{kp}(edu)$ and $Cov_{kp}(inc, edu)$ using additional data source: the China Household Finance Survey data.[3] We use the 2011, 2013 and 2015 wave, select individuals between the ages of 0 and 30, and obtain their household income and parents education levels. All incomes in the CHFS data have been transformed to the 2009 level based on the CPI index of each province from 2009 to 2015.

Finally, we determine the proportions of college applicants for each province and demographic group using the 2003 administrative data on college admissions. At last, we generate a sample of 62,140 students in total (equal to 1% of the actual number of students who took *gaokao* in 2003).

G.2 College Sample

In 2003, there were 639 four-year undergraduate colleges in China. Among them, we obtain the quality ranking, quota, tuition, cutoff scores and geographic location of a representative sample of 500 colleges, listed in Wu (2009). We scale up the actual quota of those 500 colleges

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[2] From CCSS data we verify that these variables are jointly normally distributed for the sampled students.

[3] China Household Finance Survey (CHFS) is a nationwide sample survey conducted every two years by the Survey and Research Center for China Household Finance at Southwestern University of Finance and Economics. The CHFS samples are distributed in 355 counties and 29 provinces (Tibet is excluded), covering about 30 thousand households and 90 thousand individuals in each wave.

proportionally to match the overall admission rates of all 639 four-year colleges among all applicants in 2003 (i.e., 29.4%). For each student admitted in any of these colleges, we estimate the net tuition by subtracting predicted tuition subsidy from the total tuition. The amount of tuition subsidies (scholarship and tuition waiver) is estimated using Equation (3) or (A12).

In our counterfactual analysis, we need to consider scenarios in which students have homogeneous preference orders over colleges. Homogeneous student preference only relies on the commonly perceived college quality rank ordering, $\succ_q$. In other words, it only relies on coefficients $\beta_{3,i}, \beta_{4,i}$ in Equation (6). Therefore, we construct the commonly perceived college quality rank order for each college and track, as the following:

$$HomoPrefer_{sci,j} = 2.941 * SciRank_j + 0.569 * SocRank_j \tag{A16}$$

$$HomoPrefer_{hum,j} = 0.341 * SciRank_j + 1.594 * SocRank_j \tag{A17}$$

where $HomoPrefer_{sci,j}$ is the rank ordering for college j by science students, and $HomoPrefer_{hum,j}$ is the rank ordering for college j by humanity students, and $2.941 = \hat{\beta}_{3,sci} = 2.600 + 0.341, 0.569 = \hat{\beta}_{4,sci} = 1.594 - 1.025, 0.341 = \hat{\beta}_{3,hum}, 1.594 = \hat{\beta}_{4,hum}$, where the coefficient estimated values (i.e., $\hat{\beta}_{3,i}, \hat{\beta}_{4,i}$) come from the student preference estimation results in Table 4.

Appendix H. Calculating Price Effect and Allocation Effect

Let CS_{cf} denote student surplus under the counterfactual of increased tuition subsidy or reduced travel costs. Let CS_f denote student surplus attending the college under the current policy. Define CS_1 as the student surplus under the colleges attended under current policy but facing the counterfactual tuition or distance. We can decompose the change in surplus into two terms:

$$\Delta CS = CS_{cf} - CS_f = \left(CS_{cf} - CS_1\right) + \left(CS_1 - CS_f\right), \tag{A18}$$

$CS_1 - CS_f$ is the price effect, which is the change in the student's surplus due to the change in college attributes (lower tuition or travel costs) while holding fixed the attended colleges. By construction, there is no price effect if there is no tuition or travel costs change. In the subsidy policy and distance policy, we reduce the colleges' net tuition and the college-student distance respectively. Since students have negative preference for the two attributes, these policies generate a positive "price effect".

$CS_{cf} - CS_1$ is the allocation effect, which is the difference in surplus due to the fact that students are matched to a different college under the counterfactual, while holding fixed the tuition or travel costs at the counterfactual level.