Admission Mechanisms and the Mismatch between Colleges and Students: Evidence from a Large Administrative Dataset from China*

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Abstract

This paper provides empirical evidence on how China's transition from the Boston mechanism to the Chinese parallel mechanism (a simplified version of the Deferred Acceptance mechanism), along with changes to the information available to students on their entrance exam performance when they submit their college preferences, affect the academic match between colleges and students. Using data on students admitted to Chinese colleges from 2005 to 2011, we characterize the general patterns of mismatch between colleges and students based on students' scores on China's National College Entrance Exam and find evidence of substantial overmatch and undermatch. Results from a generalized difference-in-differences model indicate that switching from the Boston mechanism to the Chinese parallel mechanism lowered the probability of mismatch by approximately 6%. Allowing students to submit their college preferences after learning their exam scores rather than before the exam reduced the probability of mismatch by 18%.

Keywords: college admissions; school-student mismatch; Chinese parallel mechanism; Boston mechanism; preference submission timing

JEL classification: I21; I23; I28

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1. Introduction

Student-college academic mismatch occurs when students' academic ability could send them to higher quality colleges, but they end up at lower quality ones, or vice versa. This type of mismatch between colleges and students can be severe (Dillon and Smith, 2017; Smith, Pender, and Howell, 2013), constraining the production of human capital and negatively affecting a society's overall welfare. To improve the match between students and colleges, policy makers around the world have experimented with various policy tools, two of the most popular of which are matching mechanisms and information campaigns.

Many cities in the United States and abroad have implemented matching systems to assign students to schools at the K-12 level. These systems involve students submitting an ordered list of schools they would like to attend, schools giving priority to students in their admission offers, and an algorithm processing application lists and priorities to assign students to schools. Cities differ in their choices of matching mechanism. For instance, Charlotte, Seattle and Barcelona use the Boston mechanism (BM), while some cities, including New York and even Boston, have adopted versions of the Deferred Acceptance mechanism (DA).

Policy makers in a number of locations have also begun implementing information campaigns in efforts to help students make better informed college choices. Broadly speaking, information in this context includes knowledge of factors affecting students' choice of college. For example, policy experiments in Charlotte, Ghana, and Montana have provided students with more information on school-level academic performance, admission standards, and student loan debts (Hastings and Weinstein, 2008; Ajayi, Friedman, and Lucas, 2017; Stoddard, Urban, and Schmeiser, 2017). Starting in 2003, China began giving high school students access to their college entrance exam scores before they submit their college choice list.

Despite the prevalence of these two types of policy reforms, debate continues as to which matching algorithm and which types of information are most useful for improving academic match. The theoretical literature has thoroughly studied the properties of different matching mechanisms, and lab experiments have been designed to validate these theoretical predictions (Abdulkadiroglu, 2013). However, empirical evidence on various mechanisms' efficiency in reducing mismatch is scarce, and even less is known about the role of information in reducing academic mismatch in centralized admission processes.

To help address these gaps in the literature, in the current paper, we use administrative data from China to empirically examine the extent of academic mismatch and analyze how matching mechanisms and information campaigns can mitigate it. Using reforms to college admission processes that took place in China between 2005 and 2011 as natural experiments, we explore student-college matching outcomes under different matching and information policies. The current study is among the first to provide empirical evidence on how different centralized matching mechanisms affect student-college match using a large administrative dataset. Our results show that the Chinese parallel mechanism (CP), a simplified version of DA, can reduce academic mismatch between colleges and students compared with BM. Our findings also highlight the critical importance of information: Allowing students to learn about their test performance before they submit their college preference lists can substantially reduce mismatch.

China's institutional background offers a few distinct advantages for our study. First, starting in the early 2000s, different provinces in China independently and gradually reformed their college admission policies. All provinces used BM to match students and colleges based on students' scores on the National College Entrance Exam (NCEE) until 2001, when Hunan province began to experiment with CP. Other provinces have since followed Hunan in adopting CP. Similar phased-in features exist in information mechanism reforms. These reforms provide sufficient exogenous variation to allow us to examine the impacts of different matching and information mechanisms on student-college mismatch.

A second advantage is the availability of population data on students' matching outcomes in China's NCEE from 2005 to 2011. Our dataset includes all students who were admitted to college during the sample period (about 16 million students), with information about students' test scores, the provinces where they took the test, and the colleges in which they enrolled. The population data provide much greater external validity than would otherwise be possible using experiments to evaluate student-college match quality under different matching mechanisms.

Finally, previous studies have estimated structural models to quantify welfare changes when switching from BM to DA (Agarwal and Somaini, 2014; Calsamiglia, Fu, and Güell, 2017; Kapor, Neilson, and Zimmerman, 2017). One challenge encountered in these studies is that it is difficult to define match quality, as the schools discussed in these contexts have preferences for many student characteristics. In China, colleges strictly prefer students with higher test scores, which makes it relatively straightforward to define mismatch between students and colleges.

We first describe patterns of matching between students and colleges in China. Following Bhattacharya and Mazumder (2011), we calculate transition probabilities for students' scores and colleges' ranking percentiles and find that there are sizeable probabilities that students with low exam scores being matched with high-ranking schools, and vice versa.

We then estimate a generalized difference-in-differences regression model to quantify the effects of different matching mechanisms and information policies on mismatch for students in first-tier colleges. Following Dillon and Smith (2017), if the gap between a student's score percentile and a college's quality percentile is greater than 20, we define it as a mismatch. Our results show that moving from BM to CP yields a 6% decrease in mismatch. Allowing students to submit their college preferences after receiving their NCEE scores rather than before they take the exam reduces mismatch by 18%. Combining the two policies achieves little additional reduction in mismatch. The use of CP coupled with post-score preference submission, currently the most popular policy bundle, achieves approximately a 25% improvement in matching efficiency.

We also test whether the policies' effects differ by subgroup. For students in first-tier colleges, students from provinces with higher admission quotas, and students in the science track, submitting preferences after the release of scores is more effective in reducing mismatch than the move to CP. In comparison, for students in second- and third-tier colleges, students from provinces with lower admission quotas, and students in the humanities track, the introduction of CP is more effective at reducing mismatch than the reform to the timing of college preference submission. We argue that the relative sizes of the policy effects depend on the available choices of colleges and chances of admission for students in different subgroups. BM punishes students with lower chances of admission more heavily if they are not admitted to their first-choice college, so transitioning to CP is more effective in reducing mismatch among these students.

We conduct a few robustness checks to address concerns about endogeneity, nonacademic factors and our definition of mismatch. We find no differential pre-existing trends between early-reform and late-reform provinces, easing concerns about provinces self-selecting into policy reforms. Further, our estimation is robust to the use of alternative college ranking systems and the inclusion of students' possible location preferences in the model. We also confirm that our findings do not change when we define mismatch using different thresholds.

Our paper contributes to a large body of literature on the matching mechanisms used in centralized matching processes. Since the seminal work by Abdulkadiroglu and Sönmez (2003), economists have studied matching systems intensively. (See a survey by Abdulkadiroglu (2013).) Chen and Kesten (2017) examined the theoretical properties of variants of DA in China. However, despite an abundance of theoretical studies, little empirical work has examined whether DA offers superior matching efficiency compared with BM in the real world. Most empirical studies have used experimental data to compare match quality under DA and BM (Chen and Sönmez, 2006; Pais and Pintér, 2008; Calsamiglia, Haeringer, and Klijn, 2010; Featherstone and Niederle, 2016). The theoretical predictions in the literature are derived under strong assumptions, and most experimental studies follow these assumptions. For instance, participants in these experiments often have complete information on everyone's ability and college preferences and are asked to choose from fewer than 10 colleges. As a result, such experiments fail to capture the complexity of real-world matching processes. High school graduates in China must compete with millions of peers and choose from thousands of colleges; they cannot fully predict everyone else's ability and preferences. Therefore, it is important to empirically examine the matching issue using actual data. The only other study with a similar empirical context was conducted by Wu and Zhong (2014), who used data on one department in one elite university in China–a much less representative sample than is provided by our dataset.

The current paper also contributes to a smaller body of literature on the role of information in college admission processes and is among the first to evaluate how changes in available information in a matching system affect match quality. Many scholars have argued that students' knowledge of their own ability and chances of college admission can be crucial to their admission outcomes. Kapor, Neilson, and Zimmerman (2017) concluded from survey data that many students have incorrect beliefs about their admission chances that affect their choice-making behavior and placement outcomes. Hoxby and Avery (2013) found that low-income students are much less likely than their higher-income peers to apply for selective colleges where they actually have a high probability of admission; they attributed this finding to students' lack of information. However, no study that we know of has examined how changing the information available to students in matching systems could affect matching outcomes. China's college admission reforms provide a unique policy experiment, enabling us to study how changing the availability of information about students' exam scores and admission probabilities could improve match quality. Lien, Zheng, and Zhong (2016) and Lien, Zheng, and Zhong (2017) analyzed this issue theoretically and experimentally from an ex-ante fairness and efficiency perspective. In contrast, we focus on ex-post matching outcomes, making a beneficial addition to their findings. Additionally, prior studies have examined several types of information provided to students, including how information on college quality, financial aid, and the returns to higher education can influence college enrollment (Hastings and Weinstein, 2008; Bettinger, Long, Oreopoulos, and Sanbonmatsu, 2012; Peter and Zambre, 2017; Stoddard, Urban, and Schmeiser, 2017); our paper, meanwhile, examines a policy focused on providing information about students' own ability, proxied by their scores on a standardized test. The only other study focused on a similar type of information was conducted by Foote, Schulkind, and Shapiro (2015), who examined the effects of students receiving information about their own college-readiness after taking the ACT on their subsequent college enrollment decisions. Our paper is distinct from theirs in two respects. First, Foote, Schulkind, and Shapiro (2015) studied students' responses in intensive margins, while we focus on responses in extensive margins. Second, we study the role of information about students' own ability in a centralized matching process, while they analyzed this issue in a decentralized admission process.

The remainder of the paper is organized as follows: Section 2 documents the institutional background details; Section 3 introduces the data and describes the patterns of mismatch; Section 4 presents our empirical strategy and results, and Section 5 concludes by describing the implication of the study's findings for research and policy.

2. Institutional Background

China's exam-based college admission system was established in 1978. All college-aspiring high school students must take the NCEE and participate in a college admission process where they are matched with colleges. The NCEE has two independent tracks-science and humanities-each of which has its own exam papers, admission quotas, and matching procedures. Students choose a track in grade 11 and take the NCEE in grade 12. The provincial educational authorities carry out administration, grading, and admission procedures separately for each track. Students' NCEE scores, their reported college preferences, and the matching algorithm, combined, determine students' admission outcomes. The Ministry of Education in China divided all the four-year colleges into three admission tiers according to their quality. Colleges admit only students with NCEE scores above the threshold for their admission tier (Davey, De Lian, and Higgins, 2007).

The college admission mechanism has two important dimensions: the timing of students' college preference submission and the rules for matching colleges and students. During the past decade, the college admission mechanism in China went through major reforms in both of these dimensions, with the main intention of reducing students' risk in the college application and admission process. There are three possible options for the timing of students' college preference submission: before taking the exam; after taking the exam but before learning the exam score; and after learning the exam score. We hereafter refer to these as pre-exam, post-exam-pre-score (or halfway) and post-score, similar to Wu and Zhong (2014). Even though provincial governments have the opportunity to change their timing options each year, it is clear that provinces are shifting away from the pre-exam and post-exam-pre-score options and increasingly adopting the post-score option. Figure 1 plots the number of provinces that adopted each option between 2005 and 2016. In 2016, all provinces adopted the post-score option.

The matching rule is the specific algorithm that matches students with colleges based on their exam scores and college preferences. As with the timing option, each province chooses its own matching algorithm. Before 2001, all provinces used BM to match students and colleges. Under BM, most colleges' quotas were filled in the first round, and it was rare for colleges to admit students who did not list that college as their first choice. If students could not get into their first-choice college, they would end up being matched with a much lower quality college, leading to significant undermatch. To protect students from this risk, in 2001 Hunan province transitioned to a CP matching system. Following Hunan, more provinces gradually adopted CP.

There are similarities and differences between the CP, BM, and DA algorithms. In the most common CP version in China, students have two parallel sets of college choices: a first-choice set of three colleges and a second-choice set of another three. When colleges process the applications in each province, they only have information on students' total NCEE score, score by subject, track, choice of major, and gender. Admission decisions highly depend on students' NCEE scores. An admission board even needs to write an official explanation if it admits a student with a lower NCEE score and rejects a student with a higher NCEE score. Students who list a college in their first-choice set receive priority over students who list the same college in their second-choice set. Assignments for colleges listed in the same choice set are temporary until all choices in that set are considered. Thus, CP lies between BM, in which every assignment is final, and DA, in which every assignment is temporary until all places are filled. CP can be considered a simplified version of DA that is less costly to implement. In DA, students have to submit their preferred order of all colleges as parallel options. In CP, students' parallel options are limited to a small number. The more parallel options allowed, the closer CP is to DA. The prohibitively high cost is the reason why the provinces did not go fully into DA. In a DA system, students have to submit their preferred order of all colleges. With more than 2,000 colleges and around 10 million students taking NCEE each year, the use of DA in China is unrealistic in practice. On the contrary, in CP students just need to order a limited number of preferred colleges (normally less than six), which requires a much smaller processing cost.

Figure 2 plots the number of provinces that chose BM and the average number of parallel school options allowed in the first tier. As Figure 2 shows, provinces in China gradually switched from BM to CP, becoming less stringent as they offered students more parallel school options. For brevity, we only present the allowed choices in the first tier as the first-tier students are the sample for our baseline analysis. In most provinces, the allowed parallel choices in each admission tier are the same, while in a few provinces they might be different.

3. Data and Stylized Patterns

3.1. Administrative Data on College Admission

To obtain information on student-college match quality, we employ a unique individual-level administrative dataset that includes all students admitted to four-year colleges in China from 2005 to 2011. It contains information on each student's county of residence, NCEE track, and NCEE score, along with the name of the college and major program to which the student was admitted. Li, Loyalka, Rozelle, Wu, and Xie (2015) used a similar dataset containing college admission results in 2003 to investigate inequalities in college access between urban and rural students in China.

Table 1 presents the number of students experiencing each combination of matching mechanism and college preference submission timing during the period of interest, amounting to a total of 16 million observations. More than five million students experienced post-score preference submission and CP, which is currently the most commonly adopted policy bundle. Over six million students submitted preferences after the release of their NCEE scores but were matched with colleges through BM. About four million students submitted preferences post-exam-pre-score and were matched via BM. It is noteworthy that not a single province adopted the combination of post-exam-pre-score submission and CP. Only one million students submitted their preferences pre-exam and were matched via BM, and even fewer students-about 150,000-submitted their preferences pre-exam and were matched via CP.

Table 2 breaks down the dataset by the tier of colleges in which students enrolled. Four million students, or approximately 6% of all students who took the NCEE during the period of interest, enrolled in first-tier colleges. They represent the top 25% achievers in the dataset. The second- and third-tier colleges each took six million students and form the remaining three quarters of our dataset.

3.2. College Quality Data

To measure college quality, following Dillon and Smith (2017), we construct a one-dimensional index using principal component analysis by combining input (e.g., educational resources) and output measures (e.g., research productivity) for each college from an administrative dataset released by the Ministry of Education. Long (2008) used a similar method to evaluate college quality in the United States. The variables we use to construct the ranking index include undergraduate faculty-student ratio, faculty's educational background, campus infrastructure, research grants, and national awards. Although several Chinese college ranking systems exist, most of them only rank selective four-year colleges. Our measure allows us to rank almost every four-year college in China, except for very few ones with key variables missing. Following Dillon and Smith (2017), we calculate percentiles for our ranking index using the size of the undergraduate student body by province and track. Instead of using the total number of undergraduates in a college as the weight, as Dillon and Smith (2017) did, we construct a separate weight for each province and track combination so that every percentile has the same number of seats in each province and track. This is because China has a quota system that predetermines how many students can be admitted to a certain college for a province and track.

One potential caveat to this approach is that we cannot fully capture all nonacademic components of students' college preferences. For example, a student may prefer to attend a low-ranking college because it is close to home. We acknowledge this limitation and examine whether our results are robust to the inclusion of some observable nonacademic factors in our model. For example, in our robustness check section, we consider the distance between a student's home and college, and we check how our results vary using other college ranking systems.

3.3. Patterns of mismatch

Scholars have used different definitions and measures to operationalize mismatch between colleges and students. To operationalize academic mismatch, Dillon and Smith (2017) looked at the difference between students' percentile in the cognitive ability distribution of college starters and the percentile of the college in a student-weighted distribution of college quality. Smith, Pender, and Howell (2013) measured mismatch in terms of whether students enroll in the most selective colleges to which they are likely to be admitted, dividing colleges into very selective, selective, somewhat selective, nonselective, two-year, and no college and using students' high school performance to predict their probability of admission at each level. Other studies have investigated student-college mismatch from other perspectives. For example, Lincove and Cortes (2016) examined the social match between students and colleges, which they defined as students attending a college with high share of students in their own racial or ethnic group.

In the current study, we focus on academic mismatch, which is fundamentally driven by a student's academic ability. We use NCEE scores as a proxy for academic ability, acknowledging that while exam scores may not fully capture students' academic ability, in the context of China, they are the best measure available and the sole criterion colleges use for admission. Similar approaches have been used in other studies examining mismatch: Dillon and Smith (2017) used scores from the Armed Forces Vocational Aptitude Battery, and Hoxby and Avery (2013) relied on SAT and ACT scores to capture students' cognitive ability. Following Dillon and Smith (2017), we measure student-college academic mismatch by observing the difference between a student's percentile in the ability distribution of college starters and the percentile of the corresponding college in a student-weighted distribution of college quality. Since most Chinese provinces design their own NCEE tests independently, and admission policies were implemented at the province-year-track level, we use students' percentile rankings within the pool of college starters in their province, year, and track. If the gap between a student's score percentile and a college's quality percentile is greater than 20, we define the student as mismatched with the college.

To describe the general patterns of student-college mismatch in China, we first adopt the nonparametric transition probabilities from Bhattacharya and Mazumder (2011). The benefit of using this approach is that the nonparametric transition probabilities may be used to compare matching differences between student subgroups. We calculate transition probabilities to describe the different rates of movement across specific percentiles of the distributions of student scores and college rankings. To facilitate comparisons with the upward movement, we consider probabilities of overmatch, where the college ranking must surpass the percentile of the student score by the amount t. In the following equation, let $F_r(\cdot)$ and $F_s(\cdot)$ denote the cumulative distribution function of the distribution of college rankings and student scores, respectively. The probability of overmatch is the probability that the college's ranking is at or above the $s+t$-th percentile of the distribution $F_r(\cdot)$, conditional on students' scores being at or below the s-th percentile of the distribution $F_s(\cdot)$. The probability of overmatch can be estimated by:

$$\text{Prob}(F_r(\text{Ranking}) \geq s+t | F_s(\text{Scores}) \leq s) = \frac{\text{Prob}(F_r(\text{Ranking}) \geq s+t, F_s(\text{Scores}) \leq s)}{\text{Prob}(F_s(\text{Scores}) \leq s)}.$$

Similarly, $\text{Prob}(F_r(\text{Ranking}) \leq s-t | F_s(\text{Scores}) \geq s)$ defines the probability of undermatch. The smaller the probability, the less distortion of the ranking-score matching mechanism. While an overmatch entails a college's ranking surpassing the percentile of a student's score by a given amount, an undermatch entails a student's score exceeding a college's ranking by a given amount. Both of these situations can be considered mismatches between colleges and students.

The standard deviations of the probabilities of overmatch and undermatch are estimated through 100 repeated simulations. Let $\{r_{i;b}, s_{i;b}\}_{i=1}^{n}$ for $b = 1,2,..,100$ be a bootstrap sample that is obtained by sampling the data $\{r_i, s_i\}_{i=1}^{n}$ randomly with replacement. For each replication $b = 1,2,..,100$, we use the bootstrap sample to calculate the probabilities of overmatch and undermatch as in the equations. The standard deviations of the probabilities of overmatch and undermatch are defined as the standard deviations of the estimated probabilities across 100 simulations, respectively.

In Table 3, we present separate estimates for students in the humanities track and the science track and the differences between them. We allow t to vary from 0 to 40 in the sets of columns in increments of 10. In each row, we condition figures on students' scores being *below* the sth percentile, where s ranges from 10 to 50 in increments of 10. Table 3 shows that students in the science track suffer more distortion than do students in the humanities track, and the differences in overmatch between students in the humanities and science tracks are more severe for those with lower test scores ($s = 10 or 20$). The probability of overmatch for students whose test scores are lower than the 10th percentile and whose school's ranking is higher than the 20th percentile is 46.1% for students in the humanities track and 59.1% for students in the science track.

To estimate undermatch probabilities, in each row of Table 4, we condition figures on students' scores being *above* the sth percentile, where s ranges from 50 to 90 in increments of 10. Table 4 indicates that students in the science track experience more distortion than do those in the humanities track, and students in the science track with higher test scores

($s = 70, 80, 90$) experience more severe mismatch than do those with lower test scores. The probability of undermatch for students whose test scores are above the 90th percentile and whose school ranking is below the 80th percentile is 24.0% for students in the humanities track and 37.4% for students in the science track.

Figure 3 plots the distribution of the differences between a student's score percentile and the admitting college's ranking percentile for students whose scores exceed the threshold for first-tier schools in 2005 and 2011. We can observe the occurrence of both undermatch and overmatch. Comparing the density plot from 2005 to that from 2011, the fat tail shrinks to the center. This graph provides initial evidence that the adoption of post-score submission and CP reduced the level of mismatch between students and colleges. In the next section, we examine impacts on the level of mismatch.

4. Empirical Strategy and Results

4.1. Baseline Results

Our baseline regression for our main results is a generalized difference-in-differences model:

$$y_{ijt} = \alpha + \beta Policy_{jt} + \delta_j + \eta_t + \gamma Controls_{ijt} + \varepsilon_{ijt}. \tag{1}$$

The outcome variable y_{ijt} is an indicator of the mismatch between students and colleges, defined as a difference of 20 between the student's score percentile and the college's rank percentile. $Policy_{jt}$ is a vector of independent variables of interest, including the timing of students' college preference submission, the matching algorithm, and their interactions. Since no provinces adopted post-exam-pre-score preference submission in combination with CP, as shown in Table 1, there are five possible policy bundles. We set the traditional pre-exam preference submission and BM combination as the base group omitted in the regression. The estimated coefficient β shows the improvement in match quality when a province transitioned from the traditional policy bundle to another. δ_j and η_t are province and year fixed effects, controlling for provincial time-invariant characteristics and nationwide yearly shocks. $Controls_{ijt}$ captures individual or county-level idiosyncratic shocks. Specifically, we include $score_{ijt}$, a student's percentile ranking among his or her province-year-track cohort, to account for heterogeneous effects by score ranking. Because of privacy policies, our data do not include students' personal information, such as gender and family background. Instead, we include population, gross domestic product (GDP), industrial output, and fiscal revenue in a student's home county in year t and a dummy variable indicating whether the county is rural or urban to control for student background characteristics. ε_{ijt} is the random error term.

Table 5 reports the baseline regression results. In the baseline regressions, we include only students who reached the first-tier enrollment threshold. The main reason for using first-tier students is that their college choices are based almost entirely on college selectivity. Compared with first-tier students, second- and third-tier students' preferences may be more influenced by nonacademic factors, such as college location, which would mean that our academic ranking of colleges may not reflect their true preferences. Another reason for restricting our analytic sample to first-tier students is that the results for these students have greater policy significance, as first-tier colleges receive more governmental resources and admit the highest achieving students. Nonetheless, we examine the results for the full sample later in our heterogeneity analysis.

The first column presents the results without any control variables. Compared with B-M, CP reduces the probability of mismatch between students and colleges by approximately 1.4 percentage points, which is consistent with theoretical predictions and experimental evidence. The magnitude of the coefficient is not trivial. The average probability of mismatch is approximately 24%, suggesting that a transition from BM to CP may account for a 6% decrease in mismatch. Switching from pre-exam preference submission to post-score preference submission reduces the probability of mismatch by 4.2 percentage points, approximately 18% of the average mismatch. This finding is consistent with those of Kapor, Neilson, and Zimmerman (2017). Increasing the accuracy of subjective beliefs about students' probability of admission decreases the probability of mismatch. The coefficient for the interaction term between CP and post-score preference submission is not statistically significant, indicating that little improvement in efficiency is achieved by combining the two policies; these two policy reforms do not reinforce each other. Compared with the base group, the gains from combining CP and post-score preference submission is nearly one quarter of the mismatch.

In Column 2, we add control variables to the baseline regression. The number of observations decreases slightly because values for some control covariates are missing from the dataset. Adding controls overall does not affect the results much, although the coefficient for CP doubles in magnitude. Columns 3 and 4 repeat the baseline regression but replace the outcome variable with indicators for undermatch and overmatch, respectively. CP reduces the probability of both undermatch and overmatch, but it is much more effective at reducing undermatch. Post-score submission is effective in reducing only the probability of undermatch. The difference in the undermatch and overmatch reduction estimates is not surprising. Since our sample here is limited to first-tier students, the probability of overmatch is quite low relative to the probability of undermatch, suggesting that the baseline results on mismatch are driven mainly by reductions in undermatch.

Table 6 presents an analysis of the heterogeneity of the policies' effects on different student subgroups. The first column presents the results for the full sample using the baseline specification with control variables. In our baseline regression, we include only first-tier students. When we perform our baseline model on the full sample, the coefficient for post-score preference submission becomes smaller but remains statistically significant. In contrast, the coefficient for CP increases. This suggests that outcomes for second- and third-tier students are more affected by the matching algorithm than the by the timing of their college preference submission.

The heterogeneity of the effects of the two policies on different subgroups may stem from the number of choices available to students in those groups. Students in the first tier have higher exam scores than those in the second and third tiers, so they are eligible for admission to more colleges. Under BM, even if their first college choice is not met, their high scores grant them enough flexibility and competitiveness in their second choices and beyond. In contrast, students in the second or third tier face a much tougher situation under BM. As their scores are relatively low, the number of colleges available to them is smaller; if they fail to receive admission to their first-choice college, not many chances exist for them in subsequent rounds of matching. For this reason, compared with their first-tier peers, students in the second and third tiers are more likely to submit risk-averse college preferences, increasing the probability of undermatch under BM. Thus, changing to CP might benefit them more than it benefits their higher-scoring peers. Increasing the number of school choices enables them to submit more precise and less risk-averse preferences, effectively reducing their probability of mismatch. Having more information about their exam scores is less effective for reducing mismatch among second- and third-tier students, as the information itself does not help increase their chances of admission.

Table 6 also presents empirical evidence on other student subgroups to support our interpretations. First, in Columns 2 and 3, we report the results by track. In China, students in the science track enjoy more seats in colleges and have more majors to choose from than do students in the humanities track. College science majors admit only high school students in the science track, while college humanities majors admit students from both tracks. In 2011, 98.9% of students in the largest science major, engineering, were from the science track in their high school, but only 51.9% of students in the largest humanities major, management, were from the humanities track in their high school. As a result, the quota for the science track is about 2.3 times larger than the quota for the humanities track, so science students have a higher chance of getting into colleges. If our explanation for the heterogeneity across tiers is correct, the relative importance of information and matching algorithm should appear a similar pattern when comparing science-track students (who have more chances for admission) and humanities-track students (who have fewer chances for admission). In Columns 2 and 3, as expected, the estimated effects of post-score preference submission are larger for students in the science track, and the estimated effects of CP are larger for students in the humanities track.

We repeat this practice for provinces with higher and lower admission quotas, dividing the baseline sample (first-tier students) by whether a student's province of origin has a quota above the median. The provincial quotas are calculated from first-tier admission data, consistent with the sample we use here. Students from high-quota provinces have more available choices and higher chances of admission than do students from low-quota provinces. If our explanation of the heterogeneity across tiers and tracks is correct, we should find that information is more important in high-quota provinces and that the matching algorithm is more important in low-quota provinces. The estimates in Columns 4 and 5 show that our suppositions are correct: CP reduces the probability of mismatch mainly for students in provinces with quotas below the median, and post-score preference submission reduces the probability of mismatch mainly for students in provinces with quotas above the median. It is noteworthy that Column 5 omits the coefficient for the CP and post-score preference submission groups, as no provinces with high quotas adopted such a policy bundle.

4.2. Robustness

We conduct several robustness checks to support the findings from our baseline regression. First, we show that our baseline results are robust to the use of alternative college ranking systems and definitions of mismatch. Second, we show that the results are not affected when we account for the nonacademic factors we are able to observe using our dataset. Finally, we estimate the dynamic effects of the admission policies to address possible concerns about endogeneity.

Table 7 shows the results' robustness to the use of different college ranking systems. In the baseline regression, we follow Dillon and Smith (2017) in constructing a one-dimensional ranking from different measures and using it to calculate student-college mismatch. This ranking system has two potential caveats. First, students' perceptions of college rankings may not match our rankings. To address this concern, we repeat our baseline estimation using the ranking system proposed by Wu (2004), a widely used ranking in China since 1993. Though educational scholars criticize the rankings for various reasons (Li, 2010), these are still the most influential rankings among high school students in China. We adopt Wu's rankings from 2004 to avoid possible endogeneity. The results of this robustness check are presented in the first column of Table 7 and are very similar to our baseline results.

The second caveat is that our rankings cannot capture heterogeneous college preferences among different student groups. For example, students from Shanghai may prefer local high-quality colleges, such as Fudan University, over the highest-ranked colleges in Beijing, Tsinghua and Peking University. Since Shanghai is China's financial capital, local students may also prefer finance-related majors over science or arts majors. However, no existing ranking system describes such complicated heterogeneity. For this reason, we use college major programs' admission scores from the NCEE among various groups of students to represent their revealed preferences. Specifically, we calculate median enrollment scores of each college-major pair in 2005 by province and track. This ranking can reveal heterogeneous preferences among students in either track from different provinces. As this ranking is calculated using the 2005 sample, linking the ranking and the students' selections in 2005 in a single regression equation could present a simultaneity issue. For this reason, we exclude the 2005 cohort from the regression. The results are presented in Column 2 of Table 7 and are essentially robust to the use of this alternative ranking system.

In Column 3 of Table 7, we adjust our definition of mismatch from a 20% gap between the student's score percentile and the college's rank percentile to a 30% gap. Our baseline results are robust to the use of this alternative definition of mismatch.

Next, we perform a robustness check to account for a major nonacademic preference that may influence students' college choices: students' preference for attending a college closer to home. If a student prefers to attend a college close to home, the gap between the student's score percentile and the college's rank percentile will not perfectly capture the student-college mismatch. To address this concern, we add a dummy variable to our baseline regression indicating whether the admitting college is in the same province as the student's home. If students' preference for attending college close to home could explain previous findings, we would see the coefficients of admission policies fall substantially and the same-province dummy variable have positive impacts on mismatch. The results are presented in Column 4 of Table 7 and show that the coefficients of admission policies remain the same as those in the baseline regression. This finding suggests that the apparent effects of the admission policies are not in fact partially driven by students' location preferences.

Table 8 presents results in which the CP dummy variable in the baseline specification is replaced with the number of college options students are allowed. According to Chen and Kesten (2017), the matching efficiency of CP increases with the number of options. When that number goes to infinity, CP becomes DA. The results in Table 8 show that increasing the number of parallel school options allowed by one decreases the probability of mismatch by 0.9 percentage points, which is consistent with the findings from Chen and Kesten (2017).

Another potential concern about our baseline regression is the issue of endogeneity. It is possible that provinces that see more benefits from CP and post-score college preference submission would have adopted the reforms earlier. To address this concern, we check for differential pre-reform trends across provinces. We use a flexible difference-in-differences model to estimate the trends of the treatment effects before and after the reform year:

$$y_{ijt} = \alpha + \sum_{\tau=-3}^{1} \beta_\tau I(YearsSincePolicy_{jt} = \tau) + \delta_j + \eta_t + \gamma Controls_{ijt} + \varepsilon_{ijt} \tag{2}$$

where $I(\cdot)$ is an indicator function and $YearsSincePolicy_{jt}$ represents the years at time t since province j transitioned from BM to CP, or from pre-exam to post-score college preference submission. $YearsSincePolicy_{jt}$ takes negative values in the years before the reform, positive values after the reform's implementation, and zero when t is the year the reform was implemented. If the parallel trend assumption holds prior to the reform, $\beta_\tau = 0$ when $\tau < 0$. Figure 4 plots these dynamic coefficients of the CP reform along the years relative to the reform event and the associated 95% confidence intervals. We find no significant pre-existing differential trends in the reduction of the mismatch probabilities, as the coefficients on three years, two years, and one year before the reform are insignificant and close to zero. Therefore, the effects in the baseline regression may be interpreted causally with confidence. The results for the information reform are very similar, and for brevity we do not include the figure.

5. Conclusion

School choice and college admission decisions have profound implications for students' educational and labor-market outcomes. For example, studies have shown that students are more likely to complete a degree if the selectivity level of the college they attend matches their academic performance (Horn, 2006; Light and Strayer, 2000). Because of the importance of student-college match, many studies have aimed either to explain the reasons students mismatch themselves with institutions (Hill and Winston, 2010; Hoxby and Avery, 2013; Smith, Pender, and Howell, 2013) or to explore match quality under different matching mechanisms. Much of the literature on matching mechanisms focuses on comparing the theoretical properties of BM and DA, and a large number of studies have used experimental data or theoretical models to assess the theoretical predictions of the two mechanisms. However, given the relatively small scale and simple settings of these experiments, it is unclear how applicable their findings are in empirical settings. It is also unclear whether reforms to the information students have at the time of their college preference submission interact with these mechanisms to improve match quality.

To provide a better understanding of the effects of matching mechanisms and information policies, in the current study, we look at assignment outcomes in China, which has one of the world's largest college admission processes. The institutional features of college admission in China allow us to causally identify two mechanisms' impacts on student-college match outcomes. CP, a matching mechanism that combines features of DA and BM, lowered the probability of mismatch by 1.4 percentage points compared with the traditional BM. Providing information about students' exam performance can also lower the probability of mismatching. In our setting, allowing students to submit preferences after learning their exam scores rather than before lowered the probability of mismatch by 4.2 percentage points. Together, these two policy changes can account for a 25% reduction in the probability of student-college mismatch observed from 2005 to 2011.

Overall, these results suggest that China's recent reforms in college admission policies significantly improve student-college match. While our main results focus on first-tier (top performing) students, our further analyses also suggest that matching mechanisms and information might affect student subgroups differently based on their own ability and choices available to them. For second- and third-tier students, students from provinces with lower admission quotas, and students in the humanities track, the move to CP is a more effective policy than providing information about exam performance. The relative sizes of the policy effects can be at least partly explained by the available choices of colleges and chances of admission. Students might be more risk-averse when having limited options and small chances of admission, leading to bigger academic mismatch. Thus, they benefit more from increased number of parallel options after transitioning from BM to CP than learning about their performance.

Due to data limitation, a number of limitations exist and worth to explore in future studies. For example, while our results show a general improvement in match quality, they do not reveal whether the reforms benefit students from different socioeconomic backgrounds equally. Research in China, the United States, and other countries suggests that students with lower socioeconomic status are more likely to mismatch themselves with colleges (Hill and Winston, 2010; Hoxby and Avery, 2013; Pallais, 2015). Therefore, it would be worthwhile to investigate the quality of matching for students by socioeconomic status under these matching mechanisms. Additionally, increasing the number of parallel school choices permitted may improve match quality. However, in China, the number of college choices increased only from three to six in most provinces. Further examination is needed to determine whether match quality would continue to improve if students were permitted more than six choices.

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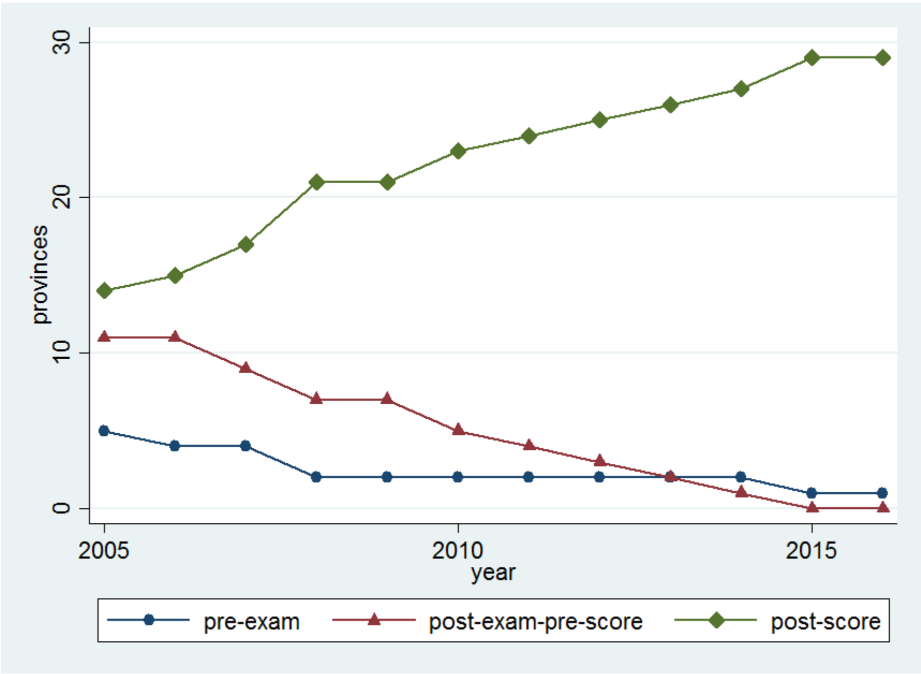

Figure 1: Provinces Adopting Various Submission Timing Policies

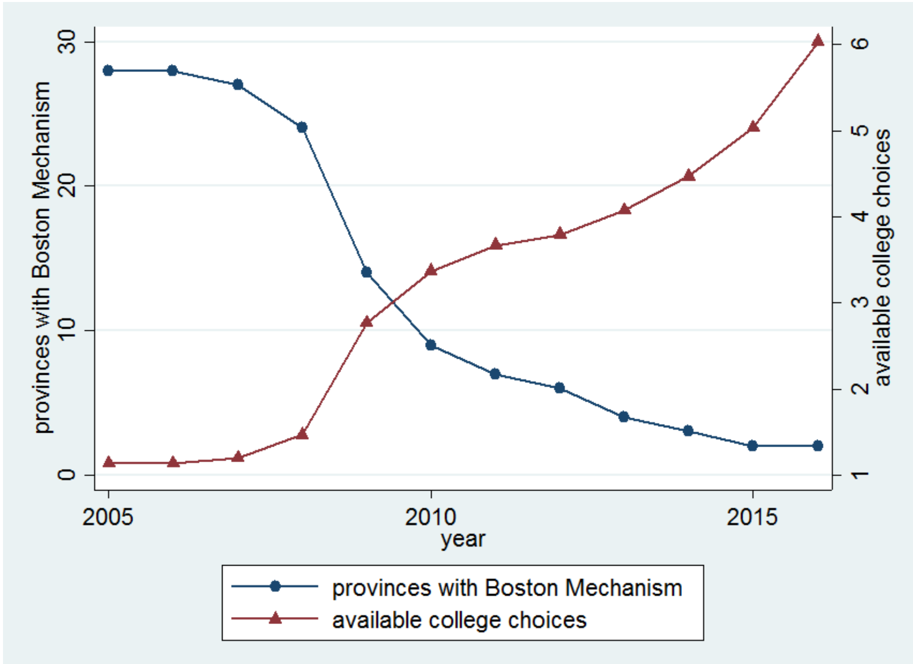

Figure 2: Provinces Using BM and Average Number of Parallel College Options

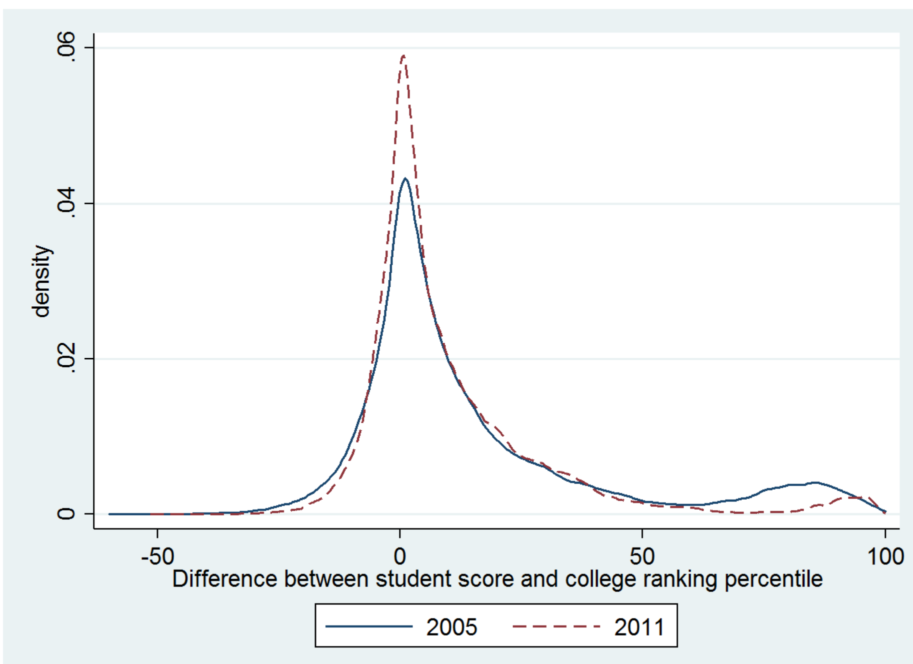

Figure 3: Distribution of Gaps Between Student Score Percentile and College Ranking Percentile

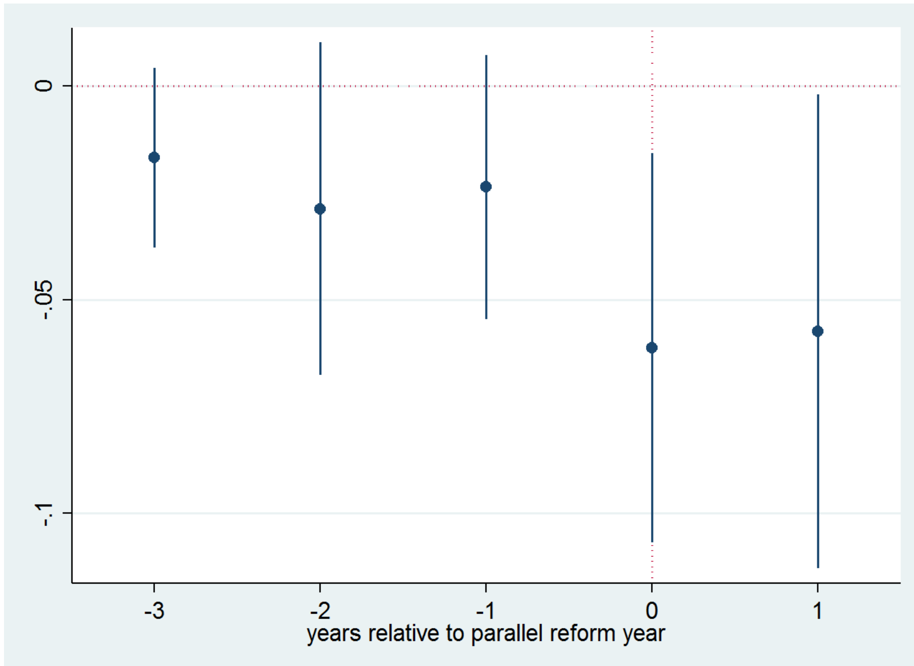

Figure 4: Dynamics of the Treatment Effects of the Chinese Parallel Reform

Table 1: Students in Each Policy Bundle, 2005-2011

Matching Mechanism	Pre-exam	Post-exam & pre-score	Post-score	Total
BM	1,081,235	4,070,767	6,589,643	11,741,645
CP,978	NA	5,396,960	5,550,938	

Table 2: Summary Statistics for Students by College Tier

Tier	Students Enrolled	Ratio	Score Percentile
First	4,203,736	6.20%	85
Second	6,863,476	10.10%	50
Third	6,225,384	9.6%	28

Note: Ratio indicates the percentage of total NCEE takers.
over the total number students who took the NCEE.

Table 3: Estimates of the Overmatching Probability for All Students

s	$t = 0$			$t = 0.1$			$t = 0.2$			$t = 0.3$			$t = 0.4$		
	Hum.	Science	H-S	Hum.	Science	H-S	Hum.	Science	H-S	Hum.	Science	H-S	Hum.	Science	H-S
0.1	0.634	0.717	-0.083	0.461	0.591	-0.130	0.346	0.430	-0.085	0.224	0.334	-0.110	0.150	0.232	-0.081
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
0.2	0.488	0.567	-0.079	0.363	0.419	-0.056	0.243	0.322	-0.080	0.163	0.230	-0.066	0.100	0.143	-0.043
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
0.3	0.389	0.441	-0.052	0.269	0.342	-0.073	0.184	0.252	-0.069	0.117	0.157	-0.041	0.070	0.111	-0.041
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
0.4	0.293	0.361	-0.068	0.206	0.271	-0.065	0.135	0.170	-0.035	0.081	0.117	-0.037	0.045	0.066	-0.021
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.5	0.230	0.284	-0.054	0.154	0.186	-0.033	0.093	0.127	-0.034	0.050	0.072	-0.022	0.018	0.029	-0.011
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: Overmatching probability is defined as $\frac{\text{Prob}(F_r(\text{Ranking}) \geq s+t, F_s(\text{Scores}) \leq s)}{\text{Prob}(F_s(\text{Scores}) \leq s)}$. Standard deviations of the parameters are computed by the standard deviation of the estimates across 100 simulations and called (simulation) standard deviations.

Table 4: Estimates of the Undermatching Probability for All Students

	$t = 0$			$t = 0.1$			$t = 0.2$			$t = 0.3$			$t = 0.4$		
s	Hum.	Science	H-S	Hum.	Science	H-S	Hum.	Science	H-S	Hum.	Science	H-S	Hum.	Science	H-S
0.5	0.249	0.302	-0.053	0.163	0.216	-0.053	0.103	0.138	-0.035	0.058	0.088	-0.030	0.026	0.036	-0.009
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.6	0.292	0.322	-0.030	0.195	0.247	-0.051	0.118	0.169	-0.051	0.071	0.102	-0.032	0.037	0.063	-0.026
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.7	0.337	0.391	-0.055	0.225	0.262	-0.036	0.138	0.192	-0.053	0.074	0.131	-0.057	0.041	0.074	-0.033
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.8	0.396	0.469	-0.073	0.247	0.317	-0.070	0.154	0.195	-0.041	0.086	0.134	-0.048	0.036	0.091	-0.054
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
0.9	0.456	0.561	-0.105	0.240	0.374	-0.133	0.140	0.223	-0.083	0.084	0.114	-0.030	0.044	0.065	-0.021
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)

Note: Undermatching probability is defined as $\frac{\text{Prob}(F_r(\text{Ranking}) \leq s+t, F_s(\text{Scores}) \geq s)}{\text{Prob}(F_s(\text{Scores}) \geq s)}$. Standard deviations of the parameters are computed by the standard deviation of the estimates across 100 simulations and called (simulation) standard deviations.

Table 5: Effects of Admission Policies on Student-College Mismatch

Variables	(1) Mismatch	(2) Mismatch	(3) Undermatch	(4) Overmatch
Post-score	-0.042**	-0.041**	-0.044**	0.003
	(0.017)	(0.018)	(0.019)	(0.002)
Post-exam but pre-score	-0.027	-0.026	-0.035	0.009*
	(0.028)	(0.028)	(0.026)	(0.005)
Chinese parallel	-0.014**	-0.029***	-0.020*	-0.008***
	(0.006)	(0.010)	(0.010)	(0.002)
Chinese parallel× post-score	0.006	0.021	0.013	0.007***
	(0.009)	(0.013)	(0.013)	(0.002)
Controls	No	Yes	Yes	Yes
Prov. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.037	0.037	0.028	0.064
Observations	4,203,736	3,855,327	3,855,327	3,855,327

Note: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. The outcome variables are indicator variables for mismatch, undermatch, and overmatch. The main independent variable is a vector of policy variables of interest, including the timing of students' college preference submissions, the matching algorithms, and their interactions. Baseline control variables include a student's percentile ranking, along with county-level population, GDP, industrial output, fiscal revenue, and urban/rural status in a student's home county. Province and year fixed effects are included in all regressions. Robust standard errors are clustered at the province level.

Table 6: Heterogeneity of the Effects of Admission Policies on Student-College Mismatch

	(1)	(2)	(3)	(4)	(5)
			Mismatch		
Sample	All 3 tiers	Science	Humanities	Low-quota	High-quota
Post-score	-0.026**	-0.042**	-0.032**	-0.005	-0.067**
	(0.011)	(0.020)	(0.015)	(0.016)	(0.023)
Post-exam but pre-score	-0.014	-0.028	-0.023	-0.013	-0.047
	(0.013)	(0.030)	(0.023)	(0.011)	(0.032)
Chinese parallel	-0.048***	-0.026**	-0.038**	-0.043***	-0.008
	(0.008)	(0.010)	(0.015)	(0.014)	(0.009)
Chinese parallel× post-score	0.023	0.016	0.036**	0.029	
	(0.014)	(0.013)	(0.017)	(0.024)	
Controls	Yes	Yes	Yes	Yes	Yes
Prov. FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.024	0.036	0.064	0.040	0.026
Observations	15,996,445	3,122,499	732,828	1,684,164	2,171,163

Note: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. The outcome variables are indicator variables for mismatch. The main independent variable is a vector of policy variables of interest, including the timing of students' college preference submissions, the matching algorithms, and their interactions. Baseline control variables include a student's percentile ranking, along with county-level population, GDP, industrial output, fiscal revenue, and urban/rural status in a student's home county. Province and year fixed effects are included in all regressions. Robust standard errors are clustered at the province level.

Table 7: Robustness Checks

	(1)	(2)	(3)	(4)
		Mismatch		
Ranking system	Shulian Wu	Enrollment score	Baseline	Baseline
Definition of mismatch	20%	20%	30%	20%
Post-score	-0.026**	-0.016**	-0.041**	-0.039**
	(0.013)	(0.007)	(0.018)	(0.017)
Post-exam but pre-score	-0.033	-0.008	-0.026	-0.025
	(0.023)	(0.011)	(0.028)	(0.026)
Chinese parallel	-0.029***	-0.033***	-0.029***	-0.023**
	(0.010)	(0.005)	(0.010)	(0.009)
Chinese parallel× post-score	0.016	0.024***	0.021	0.015
	(0.013)	(0.008)	(0.013)	(0.013)
Same province				-0.063***
				(0.013)
Controls	Yes	Yes	Yes	Yes
Prov. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.035	0.042	0.037	0.042
Observations	3,855,327	3,375,694	3,855,327	3,855,327

Note: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. The outcome variables are indicator variables for mismatch with different definitions. The main independent variable is a vector of policy variables of interest, including the timing of students' college preference submissions, the matching algorithms, and their interactions. Baseline control variables include a student's percentile ranking, along with county-level population, GDP, industrial output, fiscal revenue, and urban/rural status in a student's home county. Province and year fixed effects are included in all regressions. Robust standard errors are clustered at the province level.

Table 8: Effects of the Number of School Options on Student-College Mismatch

Variables	(1) Mismatch	(2) Undermatch	(3) Overmatch
Post-score	-0.052**	-0.052**	0.000
	(0.019)	(0.019)	(0.002)
Post-exam but pre-score	-0.025	-0.034	0.009*
	(0.027)	(0.025)	(0.005)
Number of options	-0.009**	-0.006*	-0.003***
	(0.003)	(0.004)	(0.001)
Number of options × post-score	0.009**	0.007	0.003***
	(0.004)	(0.004)	(0.001)
Controls	No	Yes	Yes
Prov. FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R-squared	0.037	0.028	0.064
Observations	3,855,327	3,855,327	3,855,327

Note: *** denotes significance at 0.01, ** at 0.05, and * at 0.1. The outcome variables are indicator variables for mismatch, undermatch, and overmatch. The main independent variable is a vector of policy variables of interest, including the timing of students' college preference submissions, the number of school options in the matching algorithms, and their interactions. Baseline control variables include a student's percentile ranking, along with county-level population, GDP, industrial output, fiscal revenue, and urban/rural status in a student's home county. Province and year fixed effects are included in all regressions. Robust standard errors are clustered at the province level.