China Economic Review 55 (2019) 143–167

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

Elite schools, magnet classes, and academic performances: Regression-discontinuity evidence from China

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A R T I C L E I N F O

Keywords:
Elite school
Magnet class
Student ability
Peer effects
Teacher effects

JEL codes:
I21 I24

A B S T R A C T

Employing a unique data from a county in rural China, we use the regression-discontinuity design to study the causal effects of elite school and magnet class enrollment. Our data contains two admissive processes, allowing us to separately examine elite school and magnet class effects on two groups of students with different abilities. Results show that enrollment in elite schools has small and insignificant effect on borderline student scores in the college entrance examination, whereas studying at a magnet class can significantly boast borderline student CEE score by 0.435 standard deviations. We provide suggestive evidence that teacher effect is roughly 40% of the magnitude of the peer effects associated with the score gain in magnet classes. We also find magnet class experience can improve the probability of entering high-quality academic universities. By comparing the effects of two cutoffs with different student abilities, our findings support the claim that the effect of elite school/magnet class enrollment depends on student abilities.

1. Introduction

In US, European, and many emerging countries, high schools are usually divided into two types: selective elite and regular. Elite schools select students from secondary schools, largely on the basis of exam scores. Many parents weigh the importance of enrolling their children into an elite school, because they believe their children could gain more from elite schoolattendance and obtain special training. The strong preference for elite schools can be attributed to two reasons. First, elite schools provide selected high-quality peers who study together. As stated in past studies, peer effects are important in improving one's academic achievement (Ding & Lehrer, 2007; Duflo, Dupas, & Kremer, 2011; Imberman, Kugler, & Sacerdote, 2012; Lavy, Silva, & Weinhardt, 2012). Second, enhanced resources, such as experienced teaching staff, are assigned to elite schools. Teacher qualification have been found to have positive effects on student performance (Chetty, Friedman, & Rockoff, 2014; Lai, Sadouolet, & Janvry, 2009). However, the empirical literature offers mixed findings regarding the effects of elite schools on students' academic performance. A most possible reason is that score gains from elite school experience may differ across student abilities. For example, highly selective elite schools admit smaller group of students with high abilities. If elite school effectonly exists among high-ability students, then researchers who examine effects on low selective schools will find minor effect.

This study attempts to analyze a unique dataset with two admission lines. Students compete for slots of two elite schools according to a uniform examination in a county. The winners are further ranked to be determined whether can enter magnet class in the two

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https://doi.org/10.1016/j.chieco.2019.03.004
Received 16 August 2018; Received in revised form 28 January 2019; Accepted 9 March 2019
Available online 13 March 2019

elite schools. Therefore, we have two score cutoffs: one reflects relatively low selective process (elite school) and the other reflects high selective process (magnet class). The two cutoffs are like a cumulative multi-cutoff (Cattaneo, Keele, Titiunik, & Vazquez-Bare, 2016). Borderline students near the magnet class cutoff have higher abilities than borderline students near the elite school cutoff. However, the two groups of students have same language, culture, and social environment. To our knowledge, this paper is the first to investigate the influences of elite schools and magnet classes on student achievement using a unified dataset. The previous studies are limited in that they cannot give a consistent explanation of the mixed results given that the cutoffs they used are not comparable to a certain extent. Our collected data enable us to compare borderline students selected by high and low enrollment standard and students with different abilities. We provide evidence that the effect of elite school/magnet class varies with student abilities.

Our research also contributes to the existing literature from three other perspectives. First, the small effect of the elite schools can arise from the possible offsetting effects masked in the average effect estimation (Anderson, Gong, Hong, & Zhang, 2016; Zhang, 2016). For example, if the effects of treatment vary across different quantiles of scores with an adverse sign, then the estimated average treatment effect can be small (Abdulkadiroglu, Angrist, & Pathak, 2014). To avoid that issue, we carry out quantile estimation to explore the treatment effects of admission to elite schools and magnet classes on the entire distribution of student achievement. Second, there should be an investigation of the effects of elite schools or magnet classes beyond those on student achievement (Dobbie & Jr, 2015; Deming, Hastings, Kane, & Staiger, 2014). Enrolling in different types of schools determines one's future choice, for example, doing research vs. being a technician. This issue is important for policy makers because it enables them to understand whether elite school and magnet class experiences can increase the number of technicians or the number of people doing research. Thus, we examine the effects of elite school and magnet class enrollment on admission to different tiers of universities. Finally, teacher and peer effects are the two possible channels that contribute to the positive effect of elite school/magnet class. The existing literature on elite school/magnet class effect do not separate the two effects. We provide suggestive evidence of the relative importance between teacher and peer effects functioning in magnet class enrollment.

In our analysis, the regression discontinuity design (hereafter, RD) is used to compare the scores of students who barely pass the admission cutoff to the scores of those who fall just below it. Students near the admission cutoff (i.e., those in the bandwidth) are assumed to be without heterogeneities. Therefore, differences between the students enrolled in elite schools/magnet classes and the unsuccessful applicants arise solely by chance. Taking into account the fuzziness of enrollment, we employ a fuzzy RD estimate approach. In the fuzzy RD, a dummy for clearing the admission cutoff is used as an instrument, after which the two-stage least square (hereafter, 2SLS) estimation is implemented. In this case, the difference in quality of education can be examined by comparing the achievement of successful applicants with that of unsuccessful participants. A quantile RD estimate is also performed to identify the effect of admission across the achievement distribution. The non-parametric RD estimation method provides robust checks for our finding.

Our analysis produces four main findings. First, the 2SLS estimates show that the marginal applicants admitted to elite schools do not perform better in the college entrance examination (hereafter, CEE) than those who are not enrolled in elite schools. In comparison, the impact of magnet classes on student performance has a positive sign: students admitted to magnet classes generally achieve 0.435 standard deviations better CEE test scores than those in regular classes. The non-parametric estimates show similar results with those in 2SLS. Therefore, by comparing the effects of two cutoffs with different selective rate, our findings show that the effects of elite school and magnet class enrollment depend on the abilities of students. In particular, studying in a good environment, including studying with high-selective qualified peers and being taught by experienced teachers, benefits high-ability students.

Second, we estimate effects on the entire distribution of the CEE scores and find that elite school enrollment has small and insignificant effects on most quantiles of the score distribution. With respect to the magnet class enrollment, we find that the score gains of arts students are mainly those on the top end of the distribution, whereas the score gains of science students are mainly those on the low end of the distribution. Hence, our result indicates that previous findings on the minor effect of elite school enrollment are not attributed to the offset of the impacts between the high- and low-achieving students.

Third, we find that the probability to pass the tier 1 university (or academic university) cutoff increases if a student has magnet class experience. Such an effect is especially significant for arts students. Because students educated in Chinese academic universities are more competitive in labor markets, our results conform to the literature showing that elite school experience has long run effect (see Clark & Del Bono, 2016; Dobbie & Jr, 2015).

Finally, with multiple cohorts in our data, we try to separate teacher effects from peer effects – the two possible mechanisms functioning in magnet class effect. Without considering the noncompliance and assuming that teachers are randomly assigned among magnet classes, we provide informative evidence that teacher effect is roughly 40% of the magnitude of the peer effects. Hence, the peer effects on CEE score would be approximately 0.31 standard deviations that are associated with score gain in magnet classes. Therefore, our results show that peer effects contribute a sizeable effect of the score gain for students studying in magnet classes.

Our findings are also of substantial policy interest: First, government should consider the trade-off between the expansion of access to education and improvement in educational quality. Expanding elite school enrollment has no effect on student achievement. By contrast, the expansion might slightly harm borderline students who are just admitted. Grouping students through a highly selective criterion can only benefit those with high abilities. Second, a growing literature suggests that intervention in high school may be too late for cost-effective human capital interventions (Cunha, Heckman, & Schennach, 2010), but we find magnet class enrollment can promote the probability of student's choice to an academic university, with the implication that it could produce meaningful long-term impacts for students.

This paper is organized as follows. The next section introduces the related literature. Section 3 introduces background on the high school entrance system in the surveyed county and our collected data. Section 4 presents the methodology and the empirical results. Section 5 provides the robustness checks and other related results. Section 6 provides interpretations for our findings. The last section concludes the paper.

2. Literature review

The empirical literature offers mixed findings regarding the effect of elite school on students' academic performance (see Chabrier, Cohodes, & Oreopoulos, 2016 for a review). Researchers provide evidence from the US, European, African, and developing countries. Many studies suggest that the gains attained from attending elite schools are minor (Abdulkadiroglu et al., 2014; Clark, 2010; Dobbie & Fryer Jr, 2014), whereas other studies find that school quality matters, arguing that elite schools have a positive effect on student achievement (Deming et al., 2014; Park, Shi, Hsieh, & An, 2015). Given the strong evidence of the positive peer effects in education and experienced teachers associated with elite schools, questioning why the effect of attending an elite school for students have produced inconsistent empirical results is natural.

Park et al. (2015) noted that the school selected for student learning is likely to be confounded by parental and familial characteristics, which influence the choice of the school and academic performance. For example, ceteris paribus, if parents give more attention to education and spend much time with their children, they would be more likely to send their children to better schools. Another explanation is that most studies compare students whose abilities are distributed near the cutoffs. However, such cutoffs may depend on school settings or other contextual factors (Abdulkadiroglu et al., 2014). Score gains may differ across student abilities, and hence the elite school cutoffs. Therefore, elite school cutoffs used in past studies are not comparable with one another. Unfortunately, few analyses on the elite school assignment exist, in which one considers varied admission cutoffs as a reflection of different students' abilities. This paper uses a dataset with two cutoffs, and we can compare the effects of the enrollment of students with different abilities.

Comparing our findings to those shown in the existing literature is useful, especially to studies in the Chinese context. Anderson et al. (2016) find that elite high schools have no effect on studen *t*-test scores in Beijing (selective rate is 27.7%). Dee and Lan (2015) find no positive effects of elite school enrollment in a city in the Inner Mongolia Autonomous Region (selective rate is 60.9%). Zhang (2016) shows little evidence of any positive academic benefits of elite school attendance in a provincial capital city in China (selective rate is 20.7%). Using data from rural counties, Park et al. (2015) discover that attending a magnet high school significantly increases the probability of being admitted to college (selective rate is 53.5%). Ma and Shi (2014) show the positive effects of magnet class attendance on students' test scores in a city in Hebei Province (selective rate is 12%). In this study, the selective rate of the examined two elite schools is approximately 67%, and selective rate of magnet classes in elite schools is 21%, we find that a significant effect exists from magnet class enrollment but not from elite school enrollment.

This paper also relates a growing body of literature analyzing the effect of attending elite schools on student long-term outcomes, such as future education and labor market income (Angrist, Cohodes, Dynarski, Pathak, & Walters, 2016; Clark & Del Bono, 2016; Dobbie & Jr, 2015; Estrada & Gignoux, 2017). For example, Clark and del Bono (2016) find that elite school attendance has positive impacts on female income. Dobbie and Jr (2015) find that six years after the admission to charter schools, males are 4.4 percentage points less likely to be incarcerated and female are 10.1 percentage points less likely to be pregnant as teenagers. We show that magnet class experience promotes the probability to enter tier 1 university. Because students educated in China's tier 1 universities have higher competitive advantage in labor markets, our results suggest that enrolling in magnet classes, to a certain extent, affects students' skill formation and further has the long-term impact on students when they enter labor markets.

3. Background and data

3.1. High school selection system of the surveyed county

In China, after a nine-year compulsory education (six-year preliminary education and three-year junior middle school), junior graduates who want to receive senior secondary education will take a high school entrance examination for admission to a senior high school. The three-year high school education is critical for students. After taking a CEE in the last year of senior high school, the result of the exam will eventually decide whether students could be enrolled in universities. CEE is one of the most influential examinations in China. As a large economic disparity exists between rural and urban areas in China, CEE is widely considered an important and relatively fair opportunity to move out of the countryside and step into the city for 5.77 hundred millions of rural peasants.

Academic high schools are set up for students who are prepared to enter college. Every year, after completing the nine-year compulsory education, students in the 9th grade take the city-level unified competitive admissions test, namely, the high school entrance examination (hereafter, HSEE). After that, students who want to obtain further education in academic high schools will enroll in elite, or regular high schools. Students who do not plan to receive education in academic high schools can enroll in vocational high schools or enter the labor market directly.

Our data were collected from the Bureau of Education of a county in Hunan Province, China. The county has a population of 832,000 and about 70% of the population are rural residents. In 2017, the per capita GDP was 18,575 CNY (2801 USD), making the county one of the poorest areas in China. According to the Bureau of Statistics of that county, enrollment is almost universal for middle school (100%) in that county, which can be attributed to the nine-year compulsory education policy in China. The policy requires all students to graduate from middle schools (Grade 9). Enrollment decreases to two-thirds for secondary high school. According to the Bureau of Education, the overall college admission rate of the county is approximately 50% for high school graduate students. Among those who received college offers, approximately 20% and 40% of students attend tier 1 and tier 2 universities, respectively.

The county we investigated has six academic high schools: two elite (Nos. 1 and 2 high schools) and four regular. The six schools

Table 1
Characteristics between elite school and regular school.

	Elite school		Regular school
	No.1 high school	No.2 high school	
	(1)	(2)	(3)
Panel A. Student performance			
Peer mean in HSEE	515.94	510.73	361.51
Peer mean in CEE	420.67	445.13	303.59
Percent of students who pass tier 1 college cutoff line (%)	24.38	24.63	21.08
Percent of students who pass tier 2 but does not pass tier 1 college cutoff (%)	33.54	30.00	26.83
Panel B. Teacher qualities			
Teacher/Student ratio	0.24	0.16	0.13
Percent of teachers with a college degree (%)	95	93	91
Percent of teachers with senior rating (%)	32	30	21
Percent of teachers with junior or higher rating (%)	74	81	63
Panel C. Educational facilities			
Book/student ratio	114.72	565.93	123.62
Computer/student ratio	0.64	0.12	0.29
Dormitory/student ratio	0.36	0.16	0.34
School square/student ratio	136.72	128.86	120.08
Number of students	1899	2452	2108

This table compares two elite schools and for four regular schools in our surveyed county. The average value of peer qualities, teacher qualities and educational facilities were reported.

all span Grades 10–12. The two elite high schools were founded in 1922 and 1939, respectively and have renowned reputation. They are considered as the two of the most famous schools in the county. The two elite schools are the only two that belong to top 10 high schools in the upper-level city in 2017 and they are both ranked at the national-level grading of Model High School (*guojiashifan gaozhong*), which is an important yardstick to measure high school quality.[1] Many parents weigh the enrollment of their children in the two elite schools because they believe the elite schools offer students with high-quality educational resources and a better chance to enter college. Our data, shown below, are consistent with these facts.

Table 1 gives a detailed description to compare the characteristics between the two elite and four regular schools. As reported in the Panel A of Table 1, the difference in average HSEE scores between the elite and regular school students exceeds 140 points, which indicates that elite school students belong to a select group with markedly higher baseline HSEE scores than their counterparts. After three years of studying, students in elite schools tend to perform better in CEE than those in regular schools. For example, the average CEE score for elite school students is 432.9 compared with 303.6 for regular school students. Table 1 also compares the fraction of students who pass tier 1 and tier 2 college cutoffs in elite and regular schools. The fraction of elite school students who pass the tier 1 college cutoff is approximately 24%, which is 3 percentage points higher than regular school students. Additionally, more than 30% of students in elite schools pass the tier 2 but does not pass tier 1 college cutoff, compared with 27% of students in regular schools.

Panel B and C of Table 1 summarize additional features, such as teacher qualities and educational facilities, of these schools. The gaps of teacher qualities in elite and regular schools are substantial. For example, more than 30% of elite school teachers obtain senior titles compared with 21% of teachers in regular schools. But students in elite schools do not enjoy more educational facilities than students in regular schools. For example, a student enrolled in No.1 High School has, on average, 115 books, fewer than that a regular school student can enjoy. Similarly, No. 2 High School has fewer computers and dormitories per student than regular schools.

Elite school enrollment is determined by student HSEE test scores and student preference. The elite school enrollment rule in our surveyed county is as follows. Applicants for Grade 9 in the county are required to rank up to three schools, usually one elite and two regular schools on an application form before the HSEE. After the examination, each school ranks all applicants who listed it as the first choice based on students' HSEE scores. If the first-choice students do not exceed the capacity of that school, it will rank students who list it as the second choice. After ranking the applicants, each school pins down a admission score line according to its capacity. The admission score line is a cutoff, which is the minimum score for the applicants to be admitted. That is, school assignment is based on student's preference and whether the student passes his/her applied school's cutoff. Note that the two elite schools are considered to be the best choices for students who are prepared to enter college. A large number of students list one of the two elite schools as their first choice on the application form. Therefore, first-choice students usually exceed the capacity of each of the two elite schools, which means that the elite schools usually reject students who list them as the second choice. If a student does not pass the cutoff of

[1] As will be discussed in the following text, 67% of high school students study in the two elite schools in the county. A possible reason for this high percentage is that the two schools raise fund to support their development by expanding the enrollment. We will discuss this issue in Section 6. The selective rate of the two elite schools examined in this study is in a similar range discussed in other papers on Chinese elite school. For example, the elite school selective rate in the research of Dee and Lan (2015) is 60.9%, whereas it is 53.5% in the paper of Park et al. (2015).

Table 2
Cutoffs of the admission to elite schools and magnet classes.

Year	Name of elite school	Number of magnet classes in elite school	Class size of magnet class	Magnet class enrollment cutoff	Elite school enrollment cutoff	Difference (3)–(4)
		(1)	(2)	(3)	(4)	(5)
2008	No.1 High School	2	57	685	625	60
	No.2 High School	2	54	665	625	40
2009	No.1 High School	2	67	700	611	89
	No.2 High School	3	57	715	621	94
2010	No.1 High School	3	64	290	250	40
	No.2 High School	3	66	300	255	35

This table presents the number of magnet classes and magnet class size in the two elite schools. It also compares cutoffs (measured by raw scores) of the two elite schools and magnet classes. In 2008 and 2009, students should take examination on seven subjects in the end of the 9th grade, while in 2010, students only take examination on three subjects in the end of the 9th grade.

the elite school which he/she applied for, then that student would end up at a regular school that he/she lists as the second or third choice on the application form.

In our surveyed county, about two thirds of applicants could win slots at one of the two elite schools every year. The high proportion of the acceptance rate is due to the fact that elite schools can raise money from the enrollment.[2] However, the expansion of the enrollment may decrease the college entrance rate, and further, reduce school reputation. To address this issue, both elite schools assign newly admitted students into magnet or regular classes. Students who win slots of the two elite schools are further ranked according to their HSEE scores. Magnet class admission score line is generated in accordance with the planned number of magnet classes in each elite school and the acceptable number of students of a class. Students who passed school assigned cutoffs study in magnet classes, whereas those who did not pass enter regular classes. As a result of this procedure, we expect that no student with HSEE scores higher than the magnet class cutoffs would be assigned to regular classes in the two elite schools. Columns 1–2 of Table 2 present detailed information of the average number of students in magnet classes and the number of magnet classes in each of the two elite schools by year. The average class size is 61. Each elite school has 3–4 magnet classes. According to our collected information from the two elite schools, experienced teachers are usually assigned to teach magnet class students. For example, teachers with senior rating is 15% higher in the magnet class than those in the regular class. However, the books, curriculum, syllabus, and duration of time that students stay in school are the same between magnet and regular class students. In our data, the magnet class enrollment rate in the elite schools is 21.1%. Hence, the fraction of students in magnet class to the overall students is 14.2%.

As expected, two cutoffs exist: one is for the admission to elite school and the other is for the admission to the magnet class. Columns 3–5 of Table 2 compare the elite school and magnet class cutoffs by school and year. Magnet class admission lines are higher than those of the elite school. On average, the former is approximately 60 points higher than the latter. Thus, magnet class enrollment is a highly selective process. We employed multi-cutoff RD framework to study if admission to elite school and magnet class can promote students' outcomes. In a standard RD design, the cutoff that determines treatment assignment is equal for all units. However, the value of the cutoff varies by unit in our data. For example, a student near a elite school cutoff may barely pass the elite school admission line by 1 point, but this student is far from magnet class cutoff. Therefore, a single running variable cannot determine the two treatment statuses.

Because magnet class cutoff is determined among elite school students. The two cutoffs in our context are like a cumulative multi-cutoff. Cattaneo et al. (2016) propose that researchers should first normalize the data around each cutoff and separately estimate the cutoff effects for the cumulative multi-cutoff. They suggest keeping observations with a score greater than or equal to the previous cutoff and smaller than the following scores. Thus, the estimated effect on each cutoff is a cumulative effect based on the previous one. Following Cattaneo et al. (2016), we separately estimate the effect of elite school or magnet class by screening data around each of the cutoff using the RD design. Our approach conforms to the standard practice in dealing with heterogeneity in the value of the cutoff. The score is normalized so that the cutoff is zero for all units. The merit of the separated estimation of elite school and magnet class effects is that it provides a clear and legible causal interpretation of the estimated coefficients: one is for elite school effect and the other is for magnet class effect conditional on the entrance in the elite school.

One caveat is that the borderline students near one cutoff may be blended with students near the other cutoff. This issue is important especially for the estimation of elite school effect. The reason is if magnet class effect is different from elite school effect, including magnet class students on the right side of elite school cutoff will bias the estimated elite school effect. The ideal situation is that the two cutoffs are far from each other, and thus, the students screened near each cutoff are less likely to be blend with students near the other cutoff. Fig. 1 shows the fraction of students enrolled in the elite schools and in the magnet classes against the HSEE score. To present the cumulative cutoffs, we code elite school students with 1 and magnet class students with 2. Each bar represents

[2] According to the Bureau of Education of that county, each student enrolled in the school should pay a tuition fee of 3000 CNY per year, equivalent to 452.5 USD.

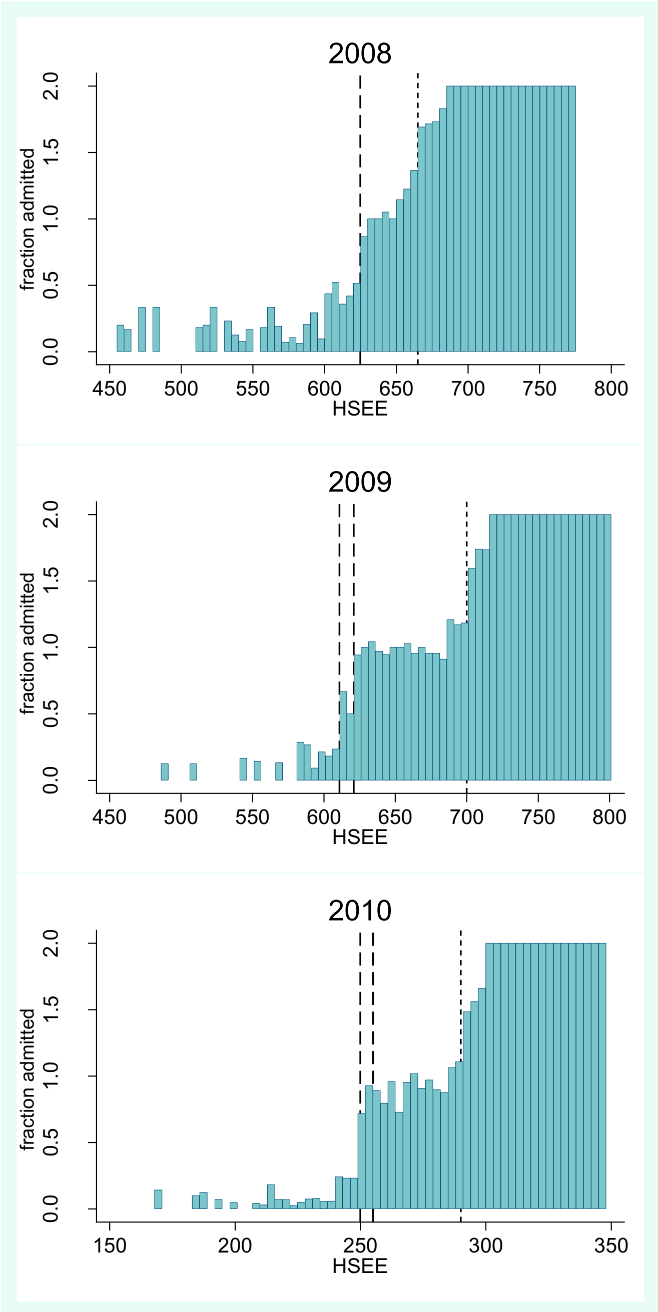

Fig. 1. Fraction of students enrolled in elite schools and magnet classes.
Notes: the dashed lines represent the cutoffs of two elite schools, and the dotted lines represent the cutoffs of magnet classes.

the fraction of students enrolled in elite schools/magnet classes in a 5-point HSEE bin. The figure shows that the two cutoffs are far from each other, implying that the students near one cutoff are far from the other one. We then carefully check our data and find that some magnet class students appear to the near right of the elite school cutoff. This fact arises from some students whose relatives are staffs of the school. However, this type of student is no more than 5% in the sample. To deal with this issue, we drop students in magnet classes when estimating elite school effect. We only keep observations with scores greater than or equal to the elite cutoff when analyzing the magnet class effect.

Fig. 2 plots the probability of the enrollment of students at elite schools and magnet classes with their HSEE scores. The left panel plots the enrollment of elite schools, and the right panel plots the enrollment of magnet classes. Plotted points indicate the conditional means of the enrollment rate in the elite high school/magnet class in one unit bandwidth. That is, we calculate the average

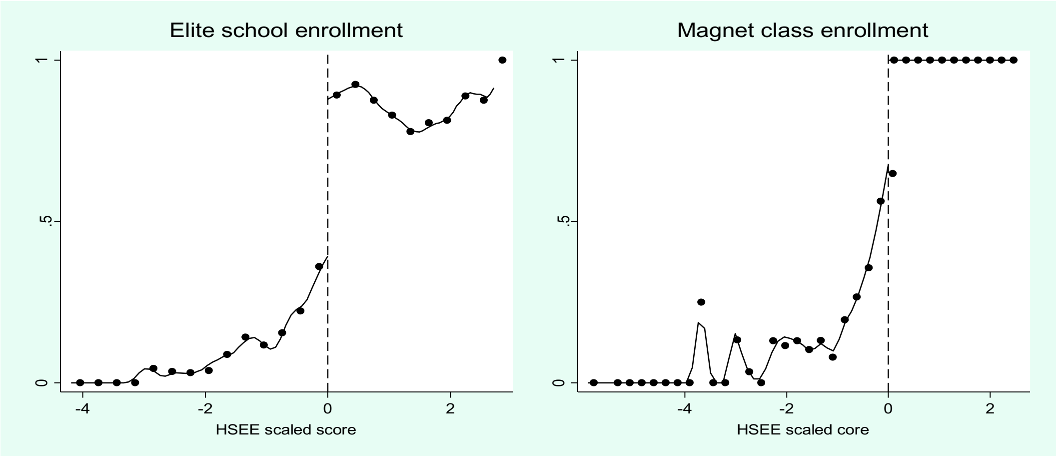

Fig. 2. Elite school and magnet class entrance probability.

outcome, $\overline{p}_{kl} = 1/N_k \sum_{i=1}^{N} e_i \cdot 1\{b_k < X_i \leq b_{k+1}\}$, $l \in \{e,m\}$, in the bins $(b_k, b_{k+1}]$, where e_i is a dummy variable which equals 1 if student i enters an elite school (a magnet class). The bandwidths used here are 0.274 for elite school enrollment and 0.235 for magnet class enrollment, which are selected according to the CCT method (Calonico, Cattaneo, & Titiunik, 2014a, 2014b). The solid line is the smoothed conditional mean function using first-degree local polynomial method with triangle kernel.

The left figure reveals a high probability of being received by elite schools if HSEE scores are above the elite school cutoff. Elite school enrollment shows an obvious jump at the cutoff. For students whose HSEE scores are higher than the threshold, the probability of enrollment at elite schools is lower than 1, indicating that some students did not list any of the elite schools on their application form. Similarly, for students whose scores are below the threshold, a positive probability exists for them to enter elite schools with the implication that certain students enter elite schools through the "back door."[3]

The right figure shows that students whose scores above the magnet class cutoff obtain seats in magnet classes with certainty. Meanwhile, those whose scores are below the cutoff are offered slots in magnet classes with a positive probability: approximately 22% students enter magnet classes even though their scores are below the cutoff line. Besides, we see an increased probability of admission in magnet classes on the left side of the cutoff with the increase in HSEE scores.

3.2. Data description

Our sample consists of students who took the HSEE exam in the 9th grade and the same students who took the CEE exam in the 12th grade. We obtained the students' demographic and score information. The Bureau of Education of the county provided the HSEE score data for students who graduated from junior middle school from 2008 to 2010 and CEE score data for students who graduated from senior high school from 2011 to 2013. The HSEE data contains the raw scores of seven subjects, namely, Chinese, Math, English, History, Geography, Physics, and Chemistry.[4] The test covers all students for Grade 9 applicants in the county who want to obtain secondary high school education. The CEE data includes score information on four subjects. All students who participate CEE should take same three subjects, namely, Chinese, English, and Math. The other subject differs between science and arts students. For science students, they take a comprehensive science test, whereas arts students take a comprehensive social science test. The HSEE and CEE scores of a student are matched by student name, age and gender. Then, the data are further merged with student demographic data, which is provided by the six high schools. Beginning with the original dataset consisting of 7356 students who participated in college entrance examinations, we dropped students majoring in arts, music, and sports.[5] We excluded students with one or more subjects having missing or zero values of the score or students with missing demographic characteristics. We also did not contain the multiple matches as we cannot identify them. Finally, we obtained 6459 matched students with HSEE and CEE scores. In the appendix (Table

[3] "Back door" means some students enter elite schools/magnet classes without passing the cutoff. This non-compliance arises from several sources, including some students are relatives of the school staffs or students' parents seek help from high-level government officials. Specifically, 261 students enter elite schools but do not pass the school admission line.

[4] In 2010, the high school entrance tested students on three subjects: Chinese, mathematics and English.

[5] Students majoring in art, music, and sport are excluded from our analysis because these students apply to universities through a special program. The score composition and university enrollment process for students through special programs are very different from the common CEE. For common CEE, the overall points of the four subjects (Chinese, mathematics, English, and comprehensive science/social science) received by a student is used for applying universities. By contrast, for students who apply for university through special programs – except for those taking Chinese, mathematics, and English tests – they are also screened by additional criteria imposed by art departments of university or some sports programs organized by official institution. The overall score weighs the importance of the special subject (i.e., art and sport), which usually accounts for more than 60%. Therefore, those students will pay much attention on the special subject, instead of the academic subjects.

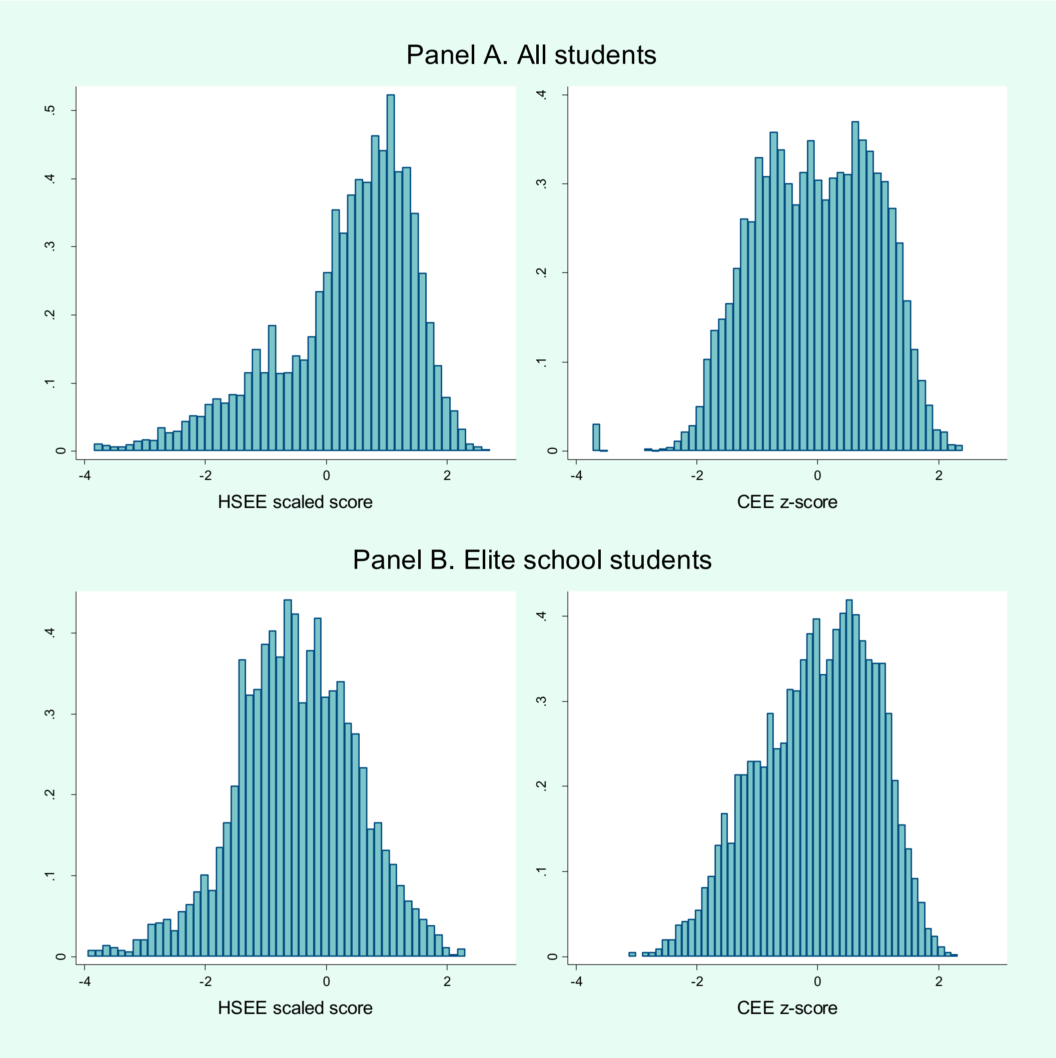

Fig. 3. Distribution of the HSEE and CEE scores.

A1), we compare students in the included and excluded samples.

In the analysis, our main dependent variable is the standardized CEE scores (or CEE z-scores), which are calculated by the distance between the CEE raw score and it's mean, then divided by the standard deviation. We further scale HSEE to the relative distance between the raw score and elite school/magnet class cutoff in units of standard deviation:

$$s_{ikt} = \frac{score_{ikt} - cutoff_{kt}}{\sigma(score_{ikt})}, \quad (1)$$

where s_{ikt} is the school-year-specific score adjusted to the elite school or magnet class cutoff line for student i in school k in year t. In addition, $score_{ikt}$ represents the HSEE raw score, $cutoff_{kt}$ denotes the elite school or magnet class cutoff, and $\sigma(score_{ikt})$ is the standard deviation of the HSEE score. The scaled HSEE is the running variable, which determines the intensity of elite school/magnet class enrollment jumps at a cutoff.

The distribution of the scaled HSEE and standardized CEE scores for all students and elite school students are plotted in Panels A and B in Fig. 3, respectively. As expected, the mean of the CEE z-score is close to zero. More than half of the students pass the elite school admission line (left figure in Panel A). In comparison, about one fourth of the students pass the magnet class admission line (left figure in Panel B).

Table 3 compares the achievement scores and demographic characteristics of students in elite schools (magnet classes) with those in regular schools (regular classes). Not surprisingly, Columns 1–3 show that students at elite schools are associated with higher baseline HSEE achievement scores than their counterparts who are at regular schools. For example, the mean HSEE score of students at elite schools is roughly 0.95 standard deviations higher than those at regular schools. The CEE scores of students after three-year studies at elite schools are also remarkably high. For example, elite school students' CEE scores are about 0.77 standard deviations

Table 3
Summary statistics.

	Elite school students v.s. Regular school students			Magnet class students v.s. Regular class students in elite schools		
	Students in regular schools	Students in elite schools	*t*-test (1)–(2)	Students in regular classes	Students in magnet classes	*t*-test (4)–(5)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Academic achievements						
Scaled HSEE score	−0.277	0.670	−0.947***	−0.123	0.421	−0.535***
	(1.228)	(0.711)		(0.781)	(0.687)	
Standardized CEE score	−0.545	0.227	−0.772***	−0.219	0.477	−0.696***
	(0.993)	(0.901)		(0.796)	(0.770)	
Panel B. Demographics						
Age	16.334	16.232	0.102***	16.320	16.181	0.139***
	(0.835)	(0.773)		(0.817)	(0.742)	
Male	0.537	0.468	0.069***	0.491	0.455	0.036**
	(0.499)	(0.499)		(0.500)	(0.498)	
Han ethnic	0.949	0.962	−0.013**	0.967	0.959	0.008
	(0.219)	(0.191)		(0.179)	(0.198)	
Urban *hukou*	0.803	0.810	−0.007	0.855	0.784	0.071***
	(0.398)	(0.392)		(0.352)	(0.411)	
Observations	2108	4351		3433	918	

This table summarizes achievements and demographics of students in the sample. Column (1)–(3) compare students who enrolled at elite schools and regular schools. Column (4)–(6) compare elite school students who enrolled at magnet classes and regular classes. Columns (3) and (6) report *t*-statistics to test the equality of the means between elite schools and regular schools. Standard deviations appear in parentheses. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

higher than those at regular schools.

Columns 4–6 compare the performance of elite school students in the magnet and regular classes. The difference in the mean HSEE achievement between students in magnet and regular classes shows a large gap. Specifically, students in magnet classes achieve scores that are 0.54 standard deviations higher than those in regular classes in their high school enrollment examination. When comparing the CEE scores between students in the magnet and regular classes, those in magnet classes enjoy an almost 0.7 standard deviations higher score than students in regular classes.

Panel B in Table 3 summarizes the demographic features of student characteristics. Students at elite schools (magnet classes) tend to be younger than those at regular schools (regular classes). In addition, girls are more likely to be admitted to elite schools and magnet classes than boys. The difference in racial composition is also found between elite and regular schools, but not between students in the magnet and regular classes. The fraction of students with urban *hukou* tends to be higher in the regular classes than those in the magnet classes.

4. Methodology and empirical results

4.1. Methodology

The model employed in this paper follows RD design in the context of the literature on treatment-effects (Imbens & Lemieux, 2008; Imbens & Wooldridge, 2009; Rubin, 1974). RD design comprises two types, namely, sharp and fuzzy. In the sharp RD design, the treatment assignment is a deterministic function of the running variable. Hence, the probability of individual receiving the treatment changes from 0 to 1 at the cutoff point. However, in our survey data, the minimum scores requirement for elite and magnet class enrollment are not completely binding, as shown in Fig. 2. Several students whose scores are below the cutoff enroll in elite schools or magnet classes, whereas a number of students whose scores are above the cutoff line do not enroll in the elite schools.[6] The fuzziness is due to several reasons. First, children prioritize enrollment in elite schools (magnet classes) if their relatives are employed in that school. Second, some parents may seek help from high-level government officials to let their children to be admitted to elite school or magnet class. Third, although they eventually passed the admission line of elite schools, a small number of students did not list the two elite schools as their first choice when they applied for high school.

For the abovementioned reasons, the fuzziness makes the treatment assignment incompletely determined by the running variable. Hence, we use the fuzzy RD design, in which the probability of receiving the treatment does not change from 0 to 1 at the cutoff point. The fuzzy RD estimator can be constructed by fitting the following 2SLS function:

[6] Note that the fuzziness of magnet classes is one-sided: elite school students whose scores pass the magnet class cutoff enter magnet classes automatically. Hence, we observe no students who passes the magnet class cutoff line are enrolled in regular classes.

$$\text{First Stage: } d_{it} = \alpha_{1t} + \delta T_{it} + f(s_{it}) + X_{it}'\Gamma_1 + \eta_{it},$$
$$\text{Second Stage: } y_{it} = \alpha_{2t} + \beta_1 \widehat{d}_{it} + f(s_{it}) + X_{it}'\Gamma_2 + u_{it}, \tag{2}$$

where d_i represents the enrollment in a elite school or magnet class for individual i and $f(s_{it})$ is a continuous polynomial function of the running variable s_{it}, which is defined by Eq. (1). As Gelman and Imbens (2018) note, high-order polynomial function in RD estimates is often poor and leads to misleading confidence intervals. Hence, we employ the local linear function. T_{it} is a dummy indicating to whether a student passes the elite school or magnet class admission cutoff; y_{it} is the outcome variable, that is, the scaled CEE scores; and X_{it} is a matrix that denotes specific and observable individual characteristics. We include age, gender, race, and *hukou* registration status. We also control class by year effect, which is denoted by α_{jt}. The coefficient of interest is β_1.

We also use a non-parametric kernel-based local polynomial approach to construct the estimate (Hahn, Todd, & Klaauw, 2001; Porter, 2003). This method differs from the parametric method in two ways: first, being conditional on the number of observations in small bins, the parametric estimates suffer from the problem the data being far from the cutoff point are given the same weight as the data near the cutoff point. Second, the non-parametric estimates adjust for additional nonlinearity by shortening the bandwidth (Abdulkadiroglu, Angrist, Dynarski, Kane, & Pathak, 2011) and give the optimal data-driven bandwidth.

We estimate the elite school and magnet class effects by pooling students to all three years. The pooled model merges three rounds of HSEE, CEE scores, and student characteristics. Hence, the estimate of the interested causal effect can be viewed as a variance-of-treatment-weighted average of year-specific effects. The standard errors are clustered at the class level.

4.2. Discontinuities and validities

Fig. 4 plots the relation between the standardized CEE scores and the running variable. The graph sheds light on our interest in the effects of elite school and magnet class enrollment. Panel A in Fig. 4 compares students' scores above and below the elite school cutoff, whereas Panel B compares students' scores above and below the magnet class cutoff. Each figure represents the CEE z-scores for arts and science students and students of the whole sample. Dots in the plots are average CEE z-scores in one unit bandwidth and the lines are from the local linear smoother to mimic the underlying variability of the data. The dashed line represents 95% confidence interval. In an effort to give a clear view, we estimate the local linear function by screening HSEE in the window from -1 to 1.

In Panel A of Fig. 4, we see that the smoothed locally linear lines show positive slopes, indicating that students with high baseline HSEE scores are associated with high CEE scores. For arts students, applicants who scored just above the elite school admission line achieved slightly lower scores than those just below the admission line. A small negative jump in CEE scores is found for arts students (left sub-figure, Panel A). No jump in CEE scores can be observed for science students (middle sub-figure, Panel A). Pooling these data still gives little evidence of discontinuity in CEE scores at the elite school cutoff points for all students who took the HSEE (right sub-figure, Panel A). In other words, these plots give little evidence of marked discontinuities in CEE scores at the elite school cutoff.

In Panel B of Fig. 4, jumps in HSEE scores at magnet class admission cutoff are all positive, indicating that admission to the magnet class is associated with obvious sharp jumps in CEE achievements. The left sub-figure presents evidence that arts students on the right side of the cutoff eventually achieved better scores in the CEE examination than those on the left; the jump is near 0.1 standard deviation. The discontinuity of CEE scores for science students is also positive and pronounced (middle sub-figure, Panel B). Both arts and science students pooled together clearly show a positive jump at the magnet class cutoff (right sub-figure, Panel B). These results imply that magnet class students tend to perform better than students in regular classes. In the next sub-section, we identify such a causal effect using regression model.

An important assumption of the RD design is that the running variable cannot be perfectly manipulated by agents. This assumption guarantees that treatment on students who manage to obtain admission to the elite school or magnet class are comparable to those who do not manage to do so, indicating that treatment status is effectively random. McCrary (2008) proposed a formal test for this issue: examining the density of the running variable. If some students are able to manipulate their treatment status, then the density of the running variable should show a kind of discontinuity at the cutoff.

Fig. 5 presents the test results proposed by McCrary (2008). Panel A shows the HSEE scores scaled over all students who took the HSEE, and Panel B shows the HSEE scores scaled over students at the two elite schools. Each panel gives the distribution, fitted value, and standard deviation of the HSEE score. The vertical line is the cutoff of elite school (Panel A) or magnet class (Panel B). The figures give little evidence of the discontinuity of the HSEE scores near zero. Density curves also appear very smooth. The *t*-test supports the null hypothesis that the score is continuous at the cutoff point, with a value of 0.89 for HSEE scores scaled over all schools and 0.69 for HSEE scores scaled over the two elite schools.

Another important assumption of the RD design is that predetermined variables, such as the demographic characteristics of students, should not show any discontinuities at the cutoff. The reason for this assumption is that these variables are determined before the treatment and should thus remain unaffected. Fig. 6 documents the test of such variables with the HSEE mean scores of students plotted on either side of the cutoff. Panel A shows the mean of age, gender, race, and *hukou* registration status of students who took the HSEE in each bin around the elite school cutoff. Panel B shows the same demographic characteristics but of elite school students near the magnet class cutoff. We screen the baseline HSEE scores in window $[-2, 2]$.[7]

In Panel A, we see that the characteristics of students do not jump at the elite school cutoff, indicating that students just above and

[7] Bin sizes are chosen by Calonico et al.'s (2014a) method.

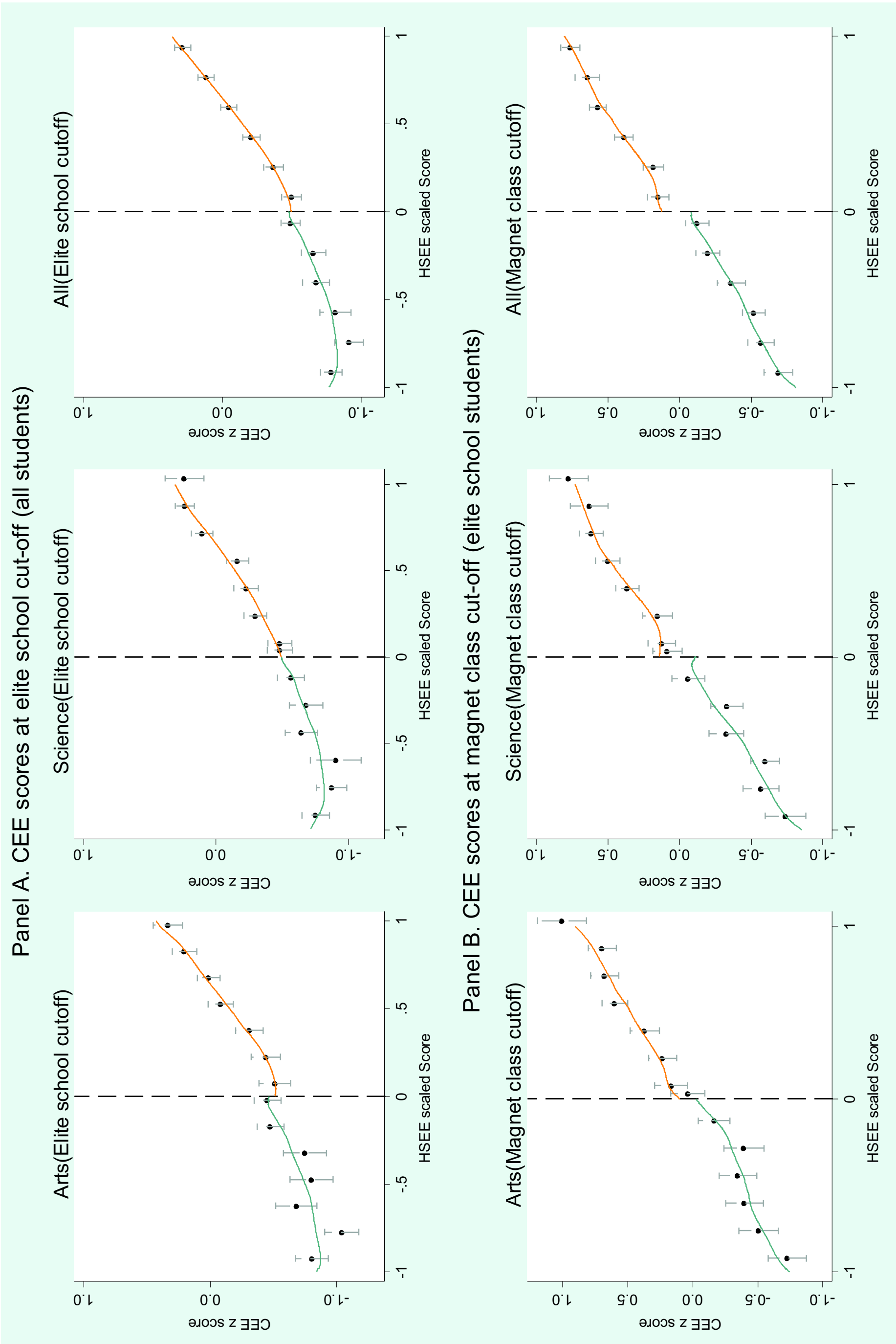

Fig. 4. CEE Scores at the elite school and magnet class cutoff points.

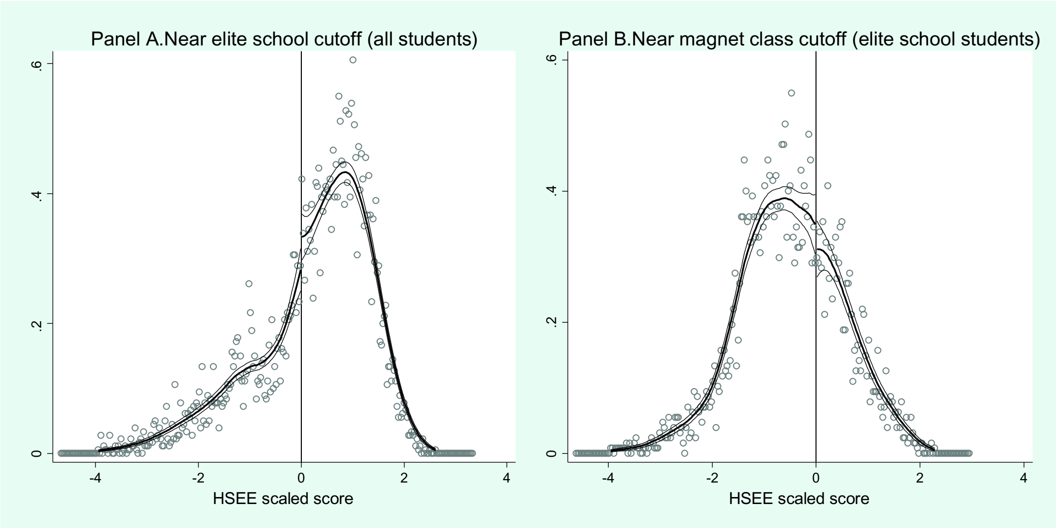

Fig. 5. McCrary test results.

just below the elite school cutoff have similar individual characteristics. A similar pattern is found in Panel B, with no jumps around the magnet class cutoff. Combined figures in the two panels together, we find the distribution of demographic characteristics of elite school applicants are quite similar to those of magnet class applicants. This result implies that, although the sample of magnet class applicants is smaller than that of elite school applicants, the distribution of individual characteristics is very similar to each other. In sum, Fig. 6 shows no demographic difference between students who fall just below the cutoff and students who barely pass the cutoff. Such finding allows us to use these predetermined individual characteristics as controls in the estimate model.

4.3. *Effects of elite school and magnet class enrollment on CEE scores*

4.3.1. *2SLS estimate*

In this part, we first use the 2SLS described by Eq. (2) to estimate the causal effects of elite school and magnet class enrollment. Then, we use the non-parametric RD method to estimate these effects.

Table 4 presents the first-stage estimates. Panel A describes high school applicants who are on either side of the elite school admission cutoff, and Panel B describes students who are on either side of the magnet class admission cutoff. The dependent variable is elite school (Panel A) or magnet class (Panel B) enrollment. The interested independent variable is an instrumental variable (IV), which is a dummy representing 1 if a student's HSEE score passes the elite school (Panel A) or magnet class (Panel B) cutoff and 0 otherwise. In other words, we expect to identify the treatment effects on students for whom elite school or magnet class attendance is influenced by the value of the running variable. We control for the age, gender, race and *hukou* registration status of the students. Class by year fixed effect is included in the estimate equation. Three bandwidths, $h = 0.1$, $h = 0.2$, and $h = 0.3$, are employed near the cutoffs to estimate the results separately. Therefore, the students concerned are those with scores in the marginal area, that is, those who barely attend elite schools/magnet classes and those who barely not attend elite schools/magnet classes.

First, results in Panel A reveal that passing the elite school cutoff has considerable predictive power in the model, in light of Fig. 2. Students with HSEE scores above the cutoff are more likely to be enrolled in an elite school. Most of the estimates are statistically different from zero. For example, when screening the sample in $[-0.1, 0.1]$ around the admission line of the elite school, Column (7) shows that students with HSEE scores exceeding the cutoff are associated with more than 31 percentage points likelihood of being enrolled in elite school. Such an effect is statistically significant at 1%. When we separate students by major, results show a similar pattern: the instrumental variable has a strong predictive power for arts and science students.

Second, the pattern shown in Panel B similarly offers the estimated effects of the instrumental variable on magnet class enrollment. Students with scores above the cutoff are more likely to acquire slots in the magnet class. All coefficients are positive and significant. On average, students with HSEE scores that pass the magnet class cutoff are associated with a roughly 30 percentage points higher likelihood of enrolling in the magnet class than those with HSEE scores that do not pass the cutoff.

The last two rows in each panel report the first stage F tests and partial R squares (Shea, 1997). Most of the F statistics are larger than 10. Furthermore, the correlation between the instrumental and endogenous variables is more than 10% when partialling out other controls. Thus, passing the elite school/magnet class cutoff is correlated with the enrollment.

Table 5 reports the effects of elite school and magnet class enrollment on student CEE scores based on 2SLS. Overall, results in Table 5 present a similar pattern as that in Fig. 4. Few estimates of the effect of enrollment at elite schools are significantly different from zero (Panel A). For arts students, Columns 1–3 show that all coefficients are negative. This result indicates that students who just enrolled at elite schools achieved less in the CEE than those who just end up at regular schools (though the results are not statistically

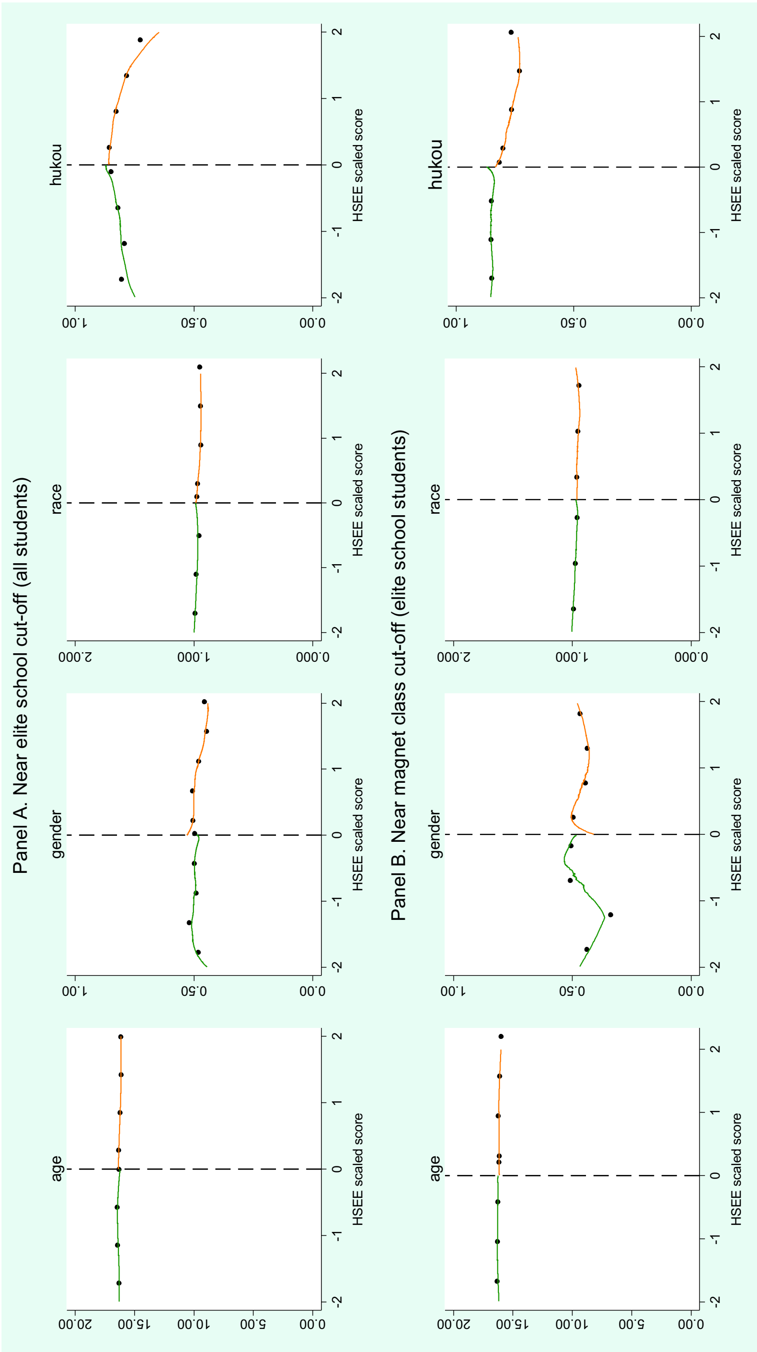

Fig. 6. Demographic characteristics and HSEE scores of students at the cutoff points.

Table 4
First stage estimates for elite school and mange class enrollment.

	Arts			Science			Whole sample		
	[−0.1, 0.1]	[−0.2, 0.2]	[−0.3, 0.3]	[−0.1, 0.1]	[−0.2, 0.2]	[−0.3, 0.3]	[−0.1, 0.1]	[−0.2, 0.2]	[−0.3, 0.3]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Elite school enrollment									
Passing elite school cutoff	0.525	0.383***	0.360***	0.291**	0.263***	0.336***	0.315***	0.307***	0.336***
	(0.337)	(0.141)	(0.113)	(0.141)	(0.077)	(0.065)	(0.101)	(0.059)	(0.047)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class by year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78	146	222	132	295	452	210	441	674
First stage *F*-test	2.43	7.38	9.86	4.26	11.67	26.72	9.73	27.07	51.11
Partial R^2	0.11	0.12	0.12	0.11	0.11	0.12	0.11	0.12	0.12
Panel B. Magnet class enrollment									
Passing magnet class cutoff	0.359***	0.328***	0.348***	0.328***	0.357***	0.304***	0.336***	0.341***	0.319***
	(0.137)	(0.094)	(0.068)	(0.105)	(0.074)	(0.058)	(0.081)	(0.057)	(0.044)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class by year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113	276	422	181	389	617	294	665	1039
First stage *F*-test	6.87	12.18	26.19	9.76	23.27	27.47	17.21	35.79	52.56
Partial R^2	0.11	0.12	0.12	0.11	0.11	0.13	0.11	0.11	0.13

This table reports the first stage regression results, where the dependent variables is elite school enrollment as shown in Panel A, and magnet class enrollment as shown in Panel B. The independent variable is the instrumental variable, which is a dummy indicating whether a student passes the corresponding cutoff. The observations are screened to different bandwidths, namely [−0.1, 0.1], [−0.2, 0.2] and [−0.3, 0.3] near the elite school or magnet class admissive score line. The control variables include the gender, age, race and *hukou* registration status of a student. Class by year fixed effect is included in the estimate equation. Standard deviations clustered at class level appear in parentheses. First stage *F*-test is the weak IV test of the significance of the IV. Partial R^2 tests the correlation between the instrument and the endogenous variable following Shea's (1997) method. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

different from zero). For example, Column 3 shows that elite school enrollment decreases CEE scores by 0.18 standard deviations at the cutoff for arts students when using an interval of ±0.3. Columns 4–6 show the effect of enrollment in elite schools on science students are small. For example, the estimate in the ±0.3 interval shows that the effect of elite school enrollment is −0.01 standard deviation, which is very close to zero and is thus not significantly different from zero. The results for all students pooled together are reported in Columns 7–9. The estimates are still small and insignificant. For example, Column 9 shows that the estimated effect of receiving elite school education is −0.09 standard deviations (s.e. = 0.18). Note that estimates in large intervals often lead to small standard errors and increased precision. The reason is that a narrow interval screens to generate a small sample size.

As for the effect of magnet class enrollment on CEE performance, 2SLS estimates for observations around the cutoff essentially oppose those for the elite school. Panel B of Table 5 shows that results are positive and are mostly significantly different from zero. Such results indicate that magnet class students earn higher scores in CEE than non-magnet class students. Take [−0.3, 0.3] interval as an example.[8] Enrollment in magnet classes boosts the CEE scores of arts students. For example, the CEE score gain for arts students who study in magnet classes is 0.43 standard deviations. Given that arts students who attend regular classes achieve an average CEE score of 400, our estimates imply that magnet class attendance can increase scores by nearly 10% (0.43 × 93/400). Results for science students are similar. Students who attend magnet classes earn an additional 0.44 standard deviations in CEE scores (Columns 6). Given that the control mean for science students is 395, the implied effect size is about 11% (0.44 × 97/395).

The estimated magnet class effect for overall students are reported in the last three columns of Panel B of Table 5. We would expect a positive effect of magnet class enrollment, which is indeed what we see here. Magnet class education is likely to boost CEE scores, ranging from 0.44 to 0.46 standard deviations, with the implication that effect size is about 10%.

4.3.2. Non-parametric estimate

One problem with the 2SLS estimator is that the consistency of 2SLS requires the IV to be exclusive, that is, $E[T,\ y|s,X] = 0$. However, we cannot directly identify the exclusion assumption of the IV. Bias from failures of the exclusion may be positive. Given that students with scores higher than the cutoff are likely to get a high score in CEE, the 2SLS estimates can be thought of as providing an upper bound to our interested causal effect. Another problem with the 2SLS estimator is that the parametric model may be corrupted by points far from the cutoff. Specifically, being conditional on the number of observations in small bins, the effects of points away from the cutoff are given the same weight as those near the cutoff. This situation means that although we assume a

[8] Panel B of Table 5 reports large standard errors estimated in the [−0.2, 0.2] window. The imprecise estimates are probably caused by the outliers in that window. We winsorize the data by replacing values which are larger than 95 percentile with the value of 95 percentile. The results reveal that the precision of the estimate is highly improved in the [−0.2, 0.2] window. For example, the estimated elite school effect for science students is 0.421 standard deviations (s.e. = 0.121) and that for the whole sample is 0.497 standard deviations (s.e. = 0.061).

Table 5
2SLS estimates for the effect of elite school and magnet class enrollment on CEE scores.

	Arts			Science			Whole sample		
	[−0.1, 0.1]	[−0.2, 0.2]	[−0.3, 0.3]	[−0.1, 0.1]	[−0.2, 0.2]	[−0.3, 0.3]	[−0.1, 0.1]	[−0.2, 0.2]	[−0.3, 0.3]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Elite school effect									
Elite school enrollment	−0.411	−0.222	−0.180	−0.521	0.010	−0.012	−0.432	−0.160	−0.094
	(0.543)	(0.521)	(0.498)	(0.737)	(0.503)	(0.123)	(0.949)	(0.451)	(0.182)
HSEE score	2.412	1.121	1.032	3.735	0.965	0.732***	2.634	1.051	0.897**
	(1.732)	(1.131)	(0.952)	(2.243)	(1.361)	(0.152)	(2.576)	(1.021)	(0.442)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class by year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78	146	222	132	295	452	210	441	674
Panel B. Magnet class effect									
Magnet class enrollment	0.433*	0.542***	0.431***	0.504**	0.449*	0.441***	0.458***	0.536***	0.435***
	(0.249)	(0.070)	(0.045)	(0.212)	(0.230)	(0.044)	(0.067)	(0.181)	(0.030)
HSEE score	0.339	−0.303	0.699**	0.284	0.648	0.645***	0.673*	0.666**	0.617***
	(0.534)	(0.398)	(0.347)	(0.543)	(0.415)	(0.234)	(0.363)	(0.335)	(0.234)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class by year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113	276	422	181	389	617	294	665	1039

Panel A reports the 2SLS regression results for elite school effect as shown in Panel A and magnet class enrollment as shown in Panel B. In the regression, the dependent variable is the standardized CEE score, and the interested independent variable is elite school enrollment (in Panel A) or magnet class enrollment (Panel B). The enrollment is instrumented using a dummy indicating whether a student passes the corresponding admissive score lines. The observations are screened to different bandwidths, namely [−0.1, 0.1], [−0.2, 0.2] and [−0.3, 0.3] near the elite school or magnet class admissive score line. The control variables include the gender, age, race and *hukou* registration status of a student. All regressions control class by year fixed effects. Standard deviations clustered at class level appear in parentheses. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

smooth underlying function on both sides of the cutoff, we do not know the exact pattern or behavior of this function. This issue would lead to the bias of the 2SLS estimator for the fuzzy RD design.

We construct the non-parametric estimates of the treatment effect with bandwidth around the cutoff. The imputed treatment effect is based on the estimate of a kernel-weighted regression function in a neighborhood of the cutoff. In this case, the estimates will be more sophisticated due to the use of weights that decrease smoothly as the distance to the cutoff point increases. In this paper, we used three data-driven bandwidth selectors: Ludwig and Miller's (Ludwig & Miller, 2007, hereafter CV) approach, Imbens and Kalyanaraman's (2012, hereafter IK) approach, and Calonico, Cattaneo, and Titiunik's (2014a, hereafter CCT) approach.[9]

Non-parametric estimated results for the effects of elite school and magnet class enrollment on the CEE scores are reported in Table 6. Panel A shows the treatment effect of the three-year elite school experience on CEE scores, and Panel B shows the treatment effect of the magnet class experience. In each panel, we report the coefficients on elite school or magnet class enrollment using the arts students sample, science students sample, and the whole sample. The three different bandwidth selection methods previously described are employed in the estimation. First, we see that CCT bandwidth selector chooses a narrower interval around the cutoff than the CV and IK selectors. Second, consistent with the estimation results from the 2SLS method, elite school experience shows little effect on student CEE scores. Precisely speaking, the coefficients are mostly negative and are not significantly different from zero. Results show similar patterns when examining elite school effects separated by major. The elite school experience has no significant impact on CEE scores for arts and science students.

Regarding to the magnet class enrollment, Panel B of Table 6 offers its effect on CEE scores. Columns 7–9 show that magnet class experience helps boost the CEE scores of students, with improvements ranging from 0.31 to 0.5 standard deviations. The coefficients are mostly positive and statistically different from zero.

For arts students, the non-parametric estimate shows that the effect of magnet class enrollment is also positive (Columns 1–3, Panel B). However, these estimates are very imprecise, as can be seen from the large standard errors, inducing the estimates are insignificant. It is noteworthy that the magnitude of coefficients for arts students is close to that estimated by 2SLS. Hence, for arts students, we do not rule out the positive effects of magnet class enrolment on the CEE scores given the commensurate effects from the 2SLS estimates. For science students, being admitted into the magnet class suggests a significant score gain in CCE scores from 0.40 to 0.49 standard deviations (Column 4–6, Panel B). This result clearly shows a large effect size that withstands different bandwidth selection methods. In particular, the estimated magnet class effect for science students under the CV selector is 0.4 standard deviations, which is very close to the 2SLS result estimated in [−0.3, 0.3] window (0.44 standard deviations).

[9] When using the CCT bandwidth-selection method, we follow the recent work of Calonico et al. (2014a), and use bias-correction techniques to handle the leading bias term. The bias correction procedure is implemented by using a higher-order local polynomial to estimate unknown derivatives and subtract them from the point estimate.

Table 6
Non-parametric estimates for elite school and magnet class enrollment on CEE scores.

	Arts			Science			Whole sample		
	CV	IK	CCT	CV	IK	CCT	CV	IK	CCT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Elite school effect									
Elite school enrollment	−0.125	−0.139	−0.120	−0.081	−0.128	0.107	−0.071	−0.046	0.021
	(0.191)	(0.198)	(0.376)	(0.171)	(0.167)	(0.440)	(0.267)	(0.237)	(0.297)
Observations	1487	879	838	1691	1387	1142	2881	2121	1903
Panel B. Magnet class effect									
Magnet class enrollment	0.283	0.474	0.352	0.398*	0.401*	0.485	0.312*	0.503*	0.413*
	(0.365)	(0.486)	(0.482)	(0.224)	(0.214)	(0.352)	(0.183)	(0.299)	(0.310)
Observations	972	813	752	933	864	739	1986	1525	1430

This table reports the non-parametric estimates of the treatment effect of elite school enrollment as shown in Panel A and magnet class enrollment as shown in Panel B, through local linear regression with bandwidth around the elite school and magnet class admissive score line. In the regression, the dependent variable is the standardized CEE score, and the interested independent variable is elite school enrollment (in Panel A) or magnet class enrollment (Panel B). The imputed treatment effect is based on the estimate of a kernel-weighted regression function in a neighborhood of the elite school or magnet class admissive score line. Three data-driven bandwidth selectors, namely CV, IK and CCT approach are used in the estimation. Standard deviations appear in parentheses. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

4.4. Examination of the entire distribution of scores

In the above analysis, we find an insignificant average treatment effect of enrollment in elite schools. This average effect may mask significant offsetting effects at different points in the distribution. For example, if the effects of treatment are different across various quantiles of scores with adverse signs, then the estimated average treatment effect may be small. To deal with this issue, we estimate the treatment effects of elite school and magnet class enrollment on the entire distribution of CEE achievement. Following Frandsen, Frölich, and Melly (2012), we employ the quantile treatment effects (QTE) estimator, a non-parametrical estimate that uses local linear techniques to estimate effects at the cutoff.

The estimated local quantile treatment effects of elite school and magnet class enrollment on CEE scores are plotted in Fig. 7. The bandwidths are chosen by Frandsen et al.'s (2012) plug-in method. The uniform kernel is used in the estimation. The points are estimated on quantiles from 0.1 to 0.9, as shown by the dashed lines in the graphs. The 90% confidence intervals are represented by the shaded area.

For arts students, the elite school effect on the lower end of the distribution is negative, whereas the effect on the upper end is approximately 0.2 standard deviations (left-sub-graph, Panel A). However, the estimated effect is precisely estimated to a reduced extent in almost each quantile of the distribution, implying that the effect is not statistically different from zero. Similarly, for science students, we find no effect of elite school enrollment. The effects on the distribution are also precisely estimated to a reduced extent, and the effects are not significantly different from zero (middle sub-graph, Panel A). The estimate results on the effect of the elite school using the whole sample are reported in the right sub-graph in Panel A. Unsurprisingly, effects on the distribution are small. Only the middle part of the distribution is relatively precisely estimated. In other words, elite school attendance has almost no impact on CEE scores when we examine the whole score distribution.

Panel B of Fig. 7 plots a similar graph through the estimation of the effects of the magnet class attendance on the distribution of CEE scores. For arts students, the left sub-graph shows that estimates are most precise for the top end of the distribution. These effects are estimated to be approximately 0.4 standard deviations, and are statistically different from zero. However, for the bottom end of the distribution, effects are small and precisely estimated to a reduced extent. For science students, the middle sub-graph shows that the effects on the lower end of the distribution are precisely estimated. The estimated effect of the magnet class ranges from 0.3 to 0.6 standard deviations. For the whole sample, the right panel indicates that the estimated effects are significantly different from zero on almost each part of the distribution. The magnitude ranges from 0.2 to 0.5 standard deviations with confidence intervals that are different from zero. The effect of the magnet class enrollment also decreases with the quantile, indicating that magnet class attendance boosts scores significantly for students on the bottom part of the CEE distribution than those on the top part.

In conclusion, the quantile estimation implies that score gains from enrollment in the magnet class are mainly exhibited by arts students on the top end of the score distribution and by science students on the bottom end of the score distribution. The different effect between arts and science students may be attributed to two possible reasons. First, learning environment affects student performance may be also relate to learning method. For example, arts learning requires students to put much effort in recitations, whereas science learning lies on the understanding of basic rudiments. Second, the difference in effect may be explained by gender composition. More girls majored in arts than boys, and more boys majored in science than girls.[10] Learning in a magnet class environment with other high-achieving girls may be most beneficial to those with scores on the top part of the distribution. Such an

[10] In the sample, 82% of students majored in arts are girls, whereas 76% of students majored in science are boys.

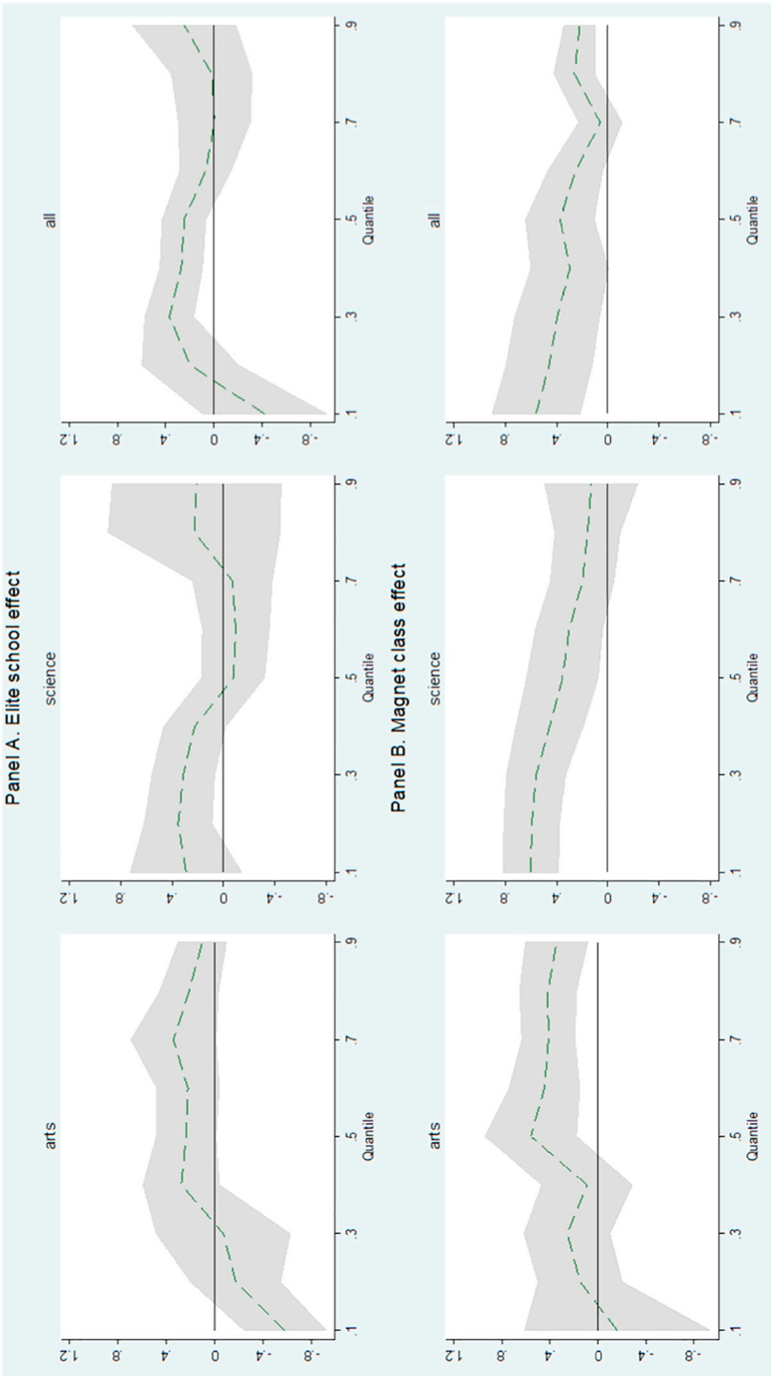

Fig. 7 . Effects of elite school and magnet class enrollments on the distribution of CEE scores.

Table 7
Effect of elite school and magnet class enrollment on three university cutoffs.

	Arts			Science			Whole sample		
	Tier 1	Tier 2	Tier 3	Tier 1	Tier 2	Tier 3	Tier 1	Tier 2	Tier 3
Panel A. Elite school: estimate in window [−0.1, 0.1]									
Elite school enrollment	0.112	0.133	0.218	−0.101	−0.121	−0.316	0.045	−0.010	−0.010
	(0.070)	(0.121)	(0.133)	(0.102)	(0.091)	(0.370)	(0.063)	(0.076)	(0.201)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78	78	78	132	132	132	210	210	210
Panel B. Magnet Class: estimate in window [−0.1, 0.1]									
Magnet Class enrollment	0.133***	−0.076	0.053	0.087*	−0.034	0.065	0.107**	−0.004	0.054
	(0.020)	(0.054)	(0.076)	(0.052)	(0.053)	(0.048)	(0.056)	(0.079)	(0.066)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113	113	113	181	181	181	294	294	294
Panel C. Elite school: estimate in window [−0.3, 0.3]									
Elite school enrollment	0.096	0.121	0.176	−0.081	−0.061	−0.240	0.049	0.015	0.028
	(0.056)	(0.106)	(0.114)	(0.065)	(0.079)	(0.233)	(0.059)	(0.048)	(0.158)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	222	222	222	452	452	452	674	674	674
Panel D. Magnet class: estimate in window [−0.3, 0.3]									
Magnet Class enrollment	0.157***	−0.062	−0.090	0.092***	−0.052	0.010	0.132**	−0.005	−0.006
	(0.009)	(0.043)	(0.060)	(0.062)	(0.046)	(0.039)	(0.021)	(0.016)	(0.034)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	422	422	422	617	617	617	1039	1039	1039

This table reports the 2SLS estimates of the treatment effect of elite school enrollment as shown in Panel A and magnet class enrollment as shown in Panel B. In the regression, the dependent variable used here is a dummy, which takes on a value of 1 if CEE score of a student passes the tier 1 university cutoff (Columns 1, 4, and 7), the tier 2 university cutoff (Columns 2, 5, and 8), and the tier 3 university cutoff (Columns 3, 6, and 9). The interested independent variable is elite school or magnet class enrollment. The enrollment is instrumented using a dummy indicating whether a student passes the corresponding admissive score lines. The control variables include the gender, age, race and *hukou* register status of a student. All regressions control class by year fixed effects. Standard deviations clustered at class level appear in parentheses. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

environment is also likely to stimulate some girls to realize the role of women and thus encourage them to aspire to become elites among their peers.

4.5. Effects of elite school and magnet class enrollment on university attendance

Universities in China are ranked by quality in three tiers. The top tier, designated as “research”, consists of 150 universities at the end of 2015. The second tier is designated as “applied” and comprises approximately 750 universities. The lowest tier is designated as “vocational” and consists of approximately 100 universities. Generally, the three groups parallel the academic ranking of the universities. High-tier universities are more likely to receive financial support from government than low-tier universities. After the CEE, each province ranks the scores of students who take the exam in that province, and defines the cutoffs for the three university tiers on the basis of the predetermined enrollment number. Students who pass the corresponding university cutoffs have high probabilities of entering a university belonging to that tier.

We determine whether enrollment in elite school or magnet class increases the probability of passing different university tiers in this sub-section. For example, if enrollment in the elite school improves the probability of passing the cutoff for tier 3 universities, even if such enrollment has no effect on the probability of passing cutoffs for tier 1 and tier 2 universities, then such result implies that studying in elite schools mostly improves the chances of students to receive undergraduate education. In contrast, if enrollment in the elite school or magnet class improves the probability of passing the cutoff for tier 1 universities, then this result implies that the enrollment would increase the number of students who conduct research.

Table 7 reports the overall results. The dependent variable used here is a dummy, which takes on a value of 1 if a CEE score of a student passes the tier 1 cutoff (Columns 1, 4, and 7), the tier 2 cutoff (Columns 2, 5, and 8), and the tier 3 cutoff (Columns 3, 6, and 9). Bandwidths are chosen in window [−0.1, 0.1] (Panel A and Panel B) and [−0.3, 0.3] (Panel C and Panel D), and 2SLS estimate coefficients on elite school (magnet class) enrollment are reported.[11]

Panel A shows that studying in elite schools mostly has no effect on the probability of passing tier 1, tier 2, and tier 3 university cutoffs, and that most coefficients are not statistically different from zero. Panel B estimates the effect of magnet class enrollment on the probability of passing the three cutoffs. The estimated effect on the probability of passing the tier 1 university cutoff is positive and statistically significant from zero. This result indicates that magnet class attendance increases the probability of students

[11] Similar results are drawn by performing the non-parametric estimate method. To save space, we only report 2SLS results here.

Table 8
Non-parametric estimates for elite school and magnet class effect by subjects.

	Chinese	Mathematics	English	Comprehensive social science	Comprehensive science
	(1)	(2)	(3)	(4)	(5)
Panel A. Elite school					
Elite school enrollment	0.141	−0.188	−0.035	−0.177	−0.021
	(0.158)	(0.168)	(0.161)	(0.299)	(0.213)
Observations	2732	2718	2653	1198	1533
Panel B. Magnet class					
Magnet class enrollment	0.158	0.413**	0.217	0.313	0.399**
	(0.117)	(0.178)	(0.156)	(0.350)	(0.161)
Observations	1877	1809	1756	633	1211

This table reports the non-parametric estimates of the treatment effect of elite school as shown in Panel A and magnet class enrollment as shown in Panel B, through local linear regression with bandwidth around the elite school (magnet class) admissive score line. In the regression, the dependent variable is the standardized CEE score, and the interested independent variable is elite school enrollment (in Panel A) or magnet class enrollment (Panel B). Each columns represents a subject. The imputed treatment effect is based on the estimate of a kernel-weighted regression function in a neighborhood of the elite school or magnet class admissive score line. Data-driven bandwidth selector approach used here is CV. Standard deviations appear in parentheses. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

enrolling in tier 1 universities. In contrast, the estimated effects are small and insignificant for passing tier 2 and tier 3 cutoffs. When we screen data in wider windows, a more precise estimate can be drawn, which can be seen in Panels C and D of Table 7. The results still show that studying in a magnet class can promote the probability to pass the tier 1 university cutoff. One possible reason is that the learning environment in the magnet class changes the notions of students. High achievers who learn together stimulate one another to pursue academic research.

In conclusion, results in Table 7 imply that enrollment in the magnet class benefits high-achieving students and improves their chances of entering tier 1 universities. This finding means that students in magnet classes tend to make academic choices when studying with high-achieving peers and being taught by high-quality teachers. Furthermore, students educated in Chinese academic universities are more competitive in labor markets. Therefore, magnet class enrollment might develop the long-term effects on students when they enter labor markets, as shown by Clark and Del Bono (2016) and Dobbie and Jr (2015).

5. Robustness check and other results

5.1. Analysis on each subject

In China, CEE scores are the overall measures of achievement that determine whether students may enroll in college. The CEE is composed of four subjects, which are Chinese, Mathematics, English, and comprehensive social science for arts students or comprehensive sciences for science students. We examine the elite school and magnet class effects by looking at each of the above subjects that constitutes the CEE scores as outcome variable.[12]

Table 8 reports the non-parametric estimate of the effect of elite school and magnet class enrollment using the CV selector by subject. Consistent with results reported in Tables 5 and 6, the results reported in Panel A of Table 8 are mostly negative and insignificant, indicating that elite school education has no effect on the achievements of applicants in these subjects. In comparison, magnet class students earn positive score gains in CEE, with coefficients on two subjects different from zero. Specifically, Columns 2 and 5 show that learning in the magnet class can significantly boost mathematics and comprehensive science scores about 0.4 standard deviations. For Chinese, English, and comprehensive social science, the outcome is strengthened by magnet class attendance, ranging from 0.22 to 0.41 standard deviations, with imprecise estimate results.

The magnet class admission estimated in Table 8 shows that score gain in Comprehensive Social Science is associated with high standard errors. This fact may explain why we find that magnet class enrollment experience does not significantly boost the CEE scores of arts students in Table 6.

5.2. Corrected standard error

In our main analysis, we cluster the standard errors at the class level to deal with the possible correlation among students' achievements in the same class. For regressions on elite school enrollment, we have 55 clusters, which is enough for statistical inference. For regressions on magnet class enrollment, we have 35 clusters that had implications in identification. To deal with this issue, we use a two-step method to make the small sample correction to the standard error. First, we apply Moulton procedure, as proposed by Angrist and Pischke (2009), to calculate the Moulton standard error. Second, we follow Cameron et al., 2008 to correct

[12] In the appendix, we test whether elite school and magnet class enrollment can predict the choice of science or arts track. We find no evidence that elite school or magnet class eWe find no evidence that elite school or magnet class experience affects track choice.

Table 9
Estimates for Elite school and magnet class effect (correct standard error).

	Arts	Science	Whole sample
	[−0.3, 0.3]	[−0.3, 0.3]	[−0.3, 0.3]
	(1)	(2)	(3)
Panel A. Elite school effect			
Elite school enrollment	−0.180	−0.012	−0.094
	(−1.205, 0.845)	(−0.265, 0.241)	(−0.457, 0.269)
Controls	Yes	Yes	Yes
Observations	222	452	674
Panel B. Magnet class effect			
Magnet class enrollment	0.431	0.441	0.435
	(0.338, 0.524)	(0.349, 0.533)	(0.374, 0.496)
Controls	Yes	Yes	Yes
Observations	422	617	1039

This table reports estimate results by correcting the standard errors. In the regression, the dependent variable is the standardized CEE score, and the interested independent variable is elite school enrollment (in Panel A) or magnet class enrollment (Panel B). We use [−0.3, 0.3] as the bandwidth. The 95% confidence interval, which corrects the small sample problem, is reported in parentheses. The control variables include the gender, age, race and *hukou* registration status of a student. All regressions control class by year fixed effects. Standard deviations clustered at class level appear in parentheses.

Moulton standard errors by magnifying the residuals by $\sqrt{K/(K-1)}$, where K is the number of classes. In this case, our statistical inference is based on t-distribution with K–2 degrees of freedom.

Table 9 reports the treatment effect separated by subject in the [−0.3, 0.3] window. For a convenient view of the significance of the estimate coefficients, a 95% confidence interval was reported. Panel A shows that the elite school enrollment has no significant impact on student CEE scores. Panel B shows that magnet class effect is significantly different from zero at the 5% level on student achievement. Such results are consistent with the findings in Tables 5 and 6, indicating that our estimates are robust.

5.3. *Test of nonrandom attrition and sample selection*

One limitation of our study is that we do not observe students with missing HSEE and students with missing characteristics. In this section, we test if the missing information is nonrandom.

The missing HSEE may arise from some individuals may take HSEE in other counties but migrate to the investigated county during their high school education, hence resulting in missing HSEE. Therefore, we regress a dummy, which equals to 1 if a student's HSEE score is missing on students' observed characteristics. Panel A of Table 10 reports results by year. The results show that most of the coefficients are statistically insignificant. Thus, our data are exempted from the sample selection problem.

The missing students' characteristics cause sample attrition. We analyze whether HSEE has predication power on sample attrition. We first add the missing sample to our main sample, and then we regress a dummy, which equals to 1 if a student has missing characteristics on his/her raw HSEE score. The results of this exercise are listed in Panel B of Table 10. In the fourth column of the table, we find no evidence that attrition is correlated with the HSEE score.

5.4. *Pure magnet class effect*

Our results so far separately examine the effects of elite school and magnet class enrollment on CEE outcomes of students. We find that for elite school students, those educated in the magnet classes score higher on their CEE score than students in regular classes. However, borderline students educated in elite school do not perform better than those educated in regular schools. In this context, determining the gains of a student enrolled in the magnet class of the elite school compared with those of students in the regular class of the regular school is interesting. We call this phenomenon the pure magnet class effect and provide some evidence to examine it. We cannot identify such an effect in the RD design because no unique running variable determines the enrollment. However, we can look at the subsamples of students with close HSEE scores but go separately to the magnet class of the elite school or the regular school.

We first exclude non-magnet class students in elite schools from the sample. Next, we constrain our sample to those whose HSEE score are higher than the magnet class admission line but do not exceed 0.5 standard deviations on the right side of the cutoff. We then compare students who are admitted to the magnet class and qualified students who could be admitted to the magnet class but end up at regular schools.

We employ OLS to examine the effect of the pure magnet class effect. In the regression, we control for baseline HSEE, gender, age, *hukou* registration status and class by year dummies. The standard errors are clustered at the class level. Although this estimate method does not provide causal inference on the magnet class effect, it allows us to compare the performance of students in the

Table 10
The test of sample selection and nonrandom attrition.

	2008	2009	2010	Overall sample
	(1)	(2)	(3)	(4)
Panel A. Sample selection				
Male	−0.030*	0.025	0.015	0.024
	(0.017)	(0.018)	(0.014)	(0.015)
Age	−0.003	0.005	−0.002	−0.001
	(0.011)	(0.009)	(0.003)	(0.008)
Han ethnic	−0.003	−0.012	−0.005	−0.006
	(0.043)	(0.033)	(0.026)	(0.035)
Urban *hukou*	−0.020	−0.028*	−0.034	−0.021
	(0.023)	(0.017)	(0.027)	(0.021)
Observations	2125	2325	2328	6778
Panel B. Non-random attrition				
HSEE raw score				−0.0009
				(0.0008)
Controls				Yes
Observations				6556

This table tests sample selection and non-random attrition problem. In Panel A, we regress a dummy, which equals to 1 if a student's HSEE score is missing on students' observed characteristics. In Panel B, we regress a dummy, which equals to 1 if a student has missing characteristics on his/her HSEE raw score. All regressions control class by year fixed effects. Standard deviations clustered at class level appear in parentheses. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

Table 11
Pure magnet class effect.

	Chinese	Mathematics	English	Comprehensive social science	Comprehensive science
	(1)	(2)	(3)	(4)	(5)
Magnet Class enrollment	0.381***	0.764***	0.658***	0.609***	0.786***
	(0.088)	(0.091)	(0.095)	(0.168)	(0.151)
HSEE	0.531***	0.405***	0.644***	0.200	0.185
	(0.139)	(0.152)	(0.153)	(0.267)	(0.238)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	300	300	300	114	186

This table uses OLS to estimate the pure magnet class effect, which compares students admitted in the magnet classes of the elite schools and qualified students who could be admitted to the magnet classes but ended up in a regular class in regular schools. Each column represents a subject. The dependent variable is the standardized CEE score and the interested independent variable is magnet class enrollment. The control variables include the gender, age, race and *hukou* registration status of a student. All regressions control class by year fixed effects. Standard deviations clustered at class level appear in parentheses. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

magnet class of the elite school with that of students in regular schools. Table 11 presents the OLS estimate results for each subject as a dependent variable.

Magnet class education is associated with a significant score gain in each subject. For Chinese, Mathematics and English, magnet class students are associated with higher scores than students in regular schools. The score gaps shown in Columns 1–3 are 0.38, 0.76, and 0.66 standard deviations, respectively. For the two specialized subjects, Columns 4 and 5 indicate the significant effects of enrolling in the magnet class. The effects are estimated to be 0.61 standard deviations for Comprehensive Arts and 0.79 standard deviations for Comprehensive Science. Compared with the outcomes reported in Table 8, these results imply a more substantial effect among students enrolling in the magnet class of the elite school, compared with students in the regular school.

5.5. Teacher effects or peer effects

As we discussed in the previous parts, the score gain from magnet class enrollment may arise both from teacher effects and peer effects. There is strong evidence of teacher effects on children's outcomes (Chetty et al., 2014). Peer effects are also found to have positive effect on children's performance (Duflo et al., 2011; Imberman et al., 2012; Lavy et al., 2012). In this sub-section, we try to provide some suggestive evidence on the comparison of the teacher effects and peer effects by separating the two effects. One merit of our data is that we collected three cohorts of students entering the same school. Araujo, Carneiro, Cruz-Aguayo, and Schady (2016) proposed that with two (or more) years of data, teacher and peer effects can be separated under the assumption that teachers and students are randomly assigned.

Table 12
Standard deviations of overall, peer effects and teacher effects of magnet class enrollment.

	2009 cohort	2010 cohort
	(1)	(2)
S.D. of overall magnet class effect	0.132	0.119
S.D. of teacher effect	0.051	0.043
S.D. of peer effects	0.122	0.109
Teacher effect/peer effects	41.8%	39.4%

This table reports the standard deviations of overall, peer effects and teacher effects of magnet class enrollment. Each columns represents students in different cohort. Students in the 2008 cohort is dropped because the estimate of S.D. of teacher effects need two years of sample.

Following Araujo et al.'s (2016) method, we first limit the sample to students in elite schools and those who are taught by the same teacher for school years 2008–2009 and 2009–2010. We then regress the standardized CEE score y_{it} on a set of class dummies and students' characteristics X_{it}. This equation is estimated in the $[-0.3, 0.3]$ window. The coefficients on magnet class dummies (denoted by γ_c) represent the overall effects associated with the magnet classes: teacher and peer effects. We focus on the variance of the overall effects, $var(\gamma_c)$. Assuming that teachers and students are randomly assigned among magnet classes, peer qualities should be uncorrelated across the two cohorts. We could calculate $\sqrt{cov(\gamma_c^t,\ \gamma_c^{t+1})}$, which is an estimate of the standard deviation of the teacher effects, purged of peer effects. Thus, the proportion of teacher effects to the overall magnet class effect is $\sqrt{cov(\gamma_c^t,\ \gamma_c^{t+1})}/\sqrt{var(\gamma_c^t)}$.

Table 12 reports the standard deviation of the overall and teacher effects of the magnet class enrollment. We estimate the standard deviation of the overall magnet class effects in the 2009 cohort as 0.132 on CEE scores and the standard deviation of teacher effects as 0.051. Thus, the SD of peer effects is $0.122 = \sqrt{0.132^2 - 0.051^2}$. This finding implies that teacher effects is 41.8% of the magnitude of the peer effects in magnet classes, implying that peer effects on CEE scores would be approximately 0.31 standard deviations. For students in the 2010 cohort, a similar result is drawn. Teacher effect is estimated to be 39.4% of the magnitude of the peer effects. In conclusion, the results in Table 12 reveal that peer effects contribute a sizeable effect of the score gain for students studying in magnet classes.

It is noted that this calculation is informative about the relative importance between peer and teacher effects. The non-compliance of students shadows the causal relation.

6. Discussion and interpretation

Our results reveal that studying with qualified peers and being taught by experienced teachers have a positive effect on student academic performance, but only for those selected by high enrollment standard and for students with high-ability. Our findings shed some light on the possible reason why the existing literature find mixed results on elite school attendance: these literature probably examined borderline students who have distinct abilities. Peer effects and teacher quality are the two main sources that contribute to the elite school/magnet class effect, and both are found to be correlated with student abilities. First, the increasing number of studies shows nonlinearities in peer effects. Specifically, high- and low-ability students may gain a difference in scores from their peers (Carrell, Sacerdote, & West, 2013; Feld & Zölitz, 2017). Second, studies also report that teacher quality is likely to have a different effect in developed and developing counties, where children have different levels of performance (Araujo et al., 2016). Using unique data, we find a positive score gain on highly selective students in the magnet class but no effect on low selective students who are barely enrolled in the elite school. This dataset offers a unified context to enable the comparison of the two groups of marginally admitted students (one group with scores near the elite school cutoff and the other with scores near the magnet class cutoff) with different abilities. Furthermore, the two groups of students were also born in the same place and were selected from given middle schools. They have the same culture and dialect.

Why do students who barely enrolled in the elite schools perform slightly worse than those who fall into regular schools (though this result is not statistically different from zero as shown in Table 5)? One possible reason is that students who barely enroll in elite school may perceive themselves as weak (Anderson et al., 2016; Pop-Eleches & Urquiola, 2013). In addition, teachers' instruction will be well suited to the top students (Duflo et al., 2011). Marginal students at elite schools are far from teachers' target level. The two effects make getting into the elite school a slightly negative effect.

7. Conclusion

In this study, we estimate elite school and magnet class enrollment using a unified dataset. The data contain two admissive processes with different score cutoffs: one is for low-selective elite high school enrollment, and the other is for high-selective magnet class enrollment. Therefore, we can estimate the causal effects of elite school and magnet class admission for the two groups of students with different abilities.

First, we find a significant difference in performance between the two groups when we compare students designated by a high score cutoff who barely enrolled in the magnet class and those who do not. Specifically, magnet class enrollment boosts the CEE scores of borderline students with 0.435 standard deviations. However, no difference in performance is observed between the elite school and non-elite school students separated by a low admission score line. These results support the claim that the score gain from high-quality educational resources, including experienced teachers and high-achieving peers may depend on student ability. Therefore, we suspect that previous mixed findings on elite school attendance are mainly due to the fact that researchers examined students with different abilities.

Second, we exclude the explanation that the minor influence of elite school attendance is attributed to the offset of effects among students at different score distributions. We find elite school enrollment has small and insignificant effects on most quantiles of the score distribution, whereas the effects of magnet class enrollment are shown to be significant on almost each part of the distribution. The estimated effect is found to be negatively correlated with the score quantile, especially for science students. This result means that magnet class attendance succeeds in significantly raising the lower end of the distribution of the CEE scores of science students.

Third, magnet class attendance increases the probability of enrollment in tier 1 universities, and thus it might change the students' choices of doing academic or vocational jobs. The magnitude of the estimates are notable. For arts students, our results suggest that the effect on enrollment in tier 1 universities is 13%, whereas the effect for science students is 8.7%. Students educated in Chinese academic universities are more competitive in labor markets. Therefore, magnet class enrollment might generate a long-term effect on students when they enter the labor markets.

Finally, we provide suggestive evidence of separating teacher effects from peer effects. Under the assumption that teachers are randomly assigned in magnet classes, we find that teacher effects are roughly of 40% the magnitude of peer effects in magnet classes, implying that peer effects on CEE score would be about 0.31 standard deviations. Therefore, our results show that peer effects contribute a sizeable effect of the score gain for students studying in magnet classes.

Acknowledgement

We are grateful to the funding support provided by the Natural Science Foundation of China, China (No. 71703055), the Ministry of Education of China, China (No. 16YJC790109), Guangzhou Planning Office of Philosophy and Social Science, China (No. 2017GZQN08), Department of Education of Guangdong Province, China (No. 2017WTSCX008), Department of Science and Technology of Guangdong Province, China (No. 2017A030310251) and Jinan University, China (17JNQN011). The views expressed in this article are solely our own.

Appendix A. Additional data description

The original dataset consists of 7356 students who participated in college entrance examinations. We drop (1) student majoring in art, music, and sport (223 observations); (2) students with one or more subjects having missing or zero values of HSEE score (319 observations); (3) students with missing demographic characteristics (97 observations); (4) multiple matches (258 observations). The screening process leaves the final sample with 6459 matched students.

Students majoring in art, music, and sport are excluded from our analysis because they apply to universities through a special program. The score composition and university enrollment process for students applying in special programs are very different from the common CEE. For students participating in common CEE, the overall points of the four subjects (Chinese, mathematics, English, and comprehensive science/social science) received by the students is used for applying for universities.[13] By contrast, students who apply for university though special programs – except for taking Chinese, mathematics, and English tests – are also screened using additional criteria imposed by some art departments of university or sports programs organized by official institutions. The overall score weighs the special subject (i.e., art or sport), which usually accounts for more than 60%. Therefore, those students will pay more attention on the special subject than the academic subjects.

Students with missing HSEE scores and individual characteristics are marked as invalid observations. We match HSEE and CEE scores using student's name and gender. Hence, students with duplicated name and gender cannot be precisely matched and thus are dropped.

Table A1 presents the raw HSEE scores, raw CEE scores, and demographic characteristics between the included sample and excluded sample. The characteristics of the students are similar between the included and excluded samples. For HSEE and CEE scores, the excluded students achieve lower scores than included students, arising from the fact that students majoring in art, music, and sport perform worse than other students.

[13] The total point for Chinese, mathematics, and English is 150. The total point for comprehensive science or arts is 300.

Table A1
Comparison between included and excluded samples.

	Included sample	Excluded sample	(2)–(1)
	(1)	(2)	
Raw HSEE score	413.18	346.24	−66.94***
	(74.39)	(67.25)	
Observations	6459	320	
Raw CEE score	409.25	322.11	−87.14***
	(105.25)	(96.68)	
Observations	6459	320	
Age	16.283	16.431	0.148
	(0.811)	(0.833)	
Observations	6459	542	
Male	0.503	0.500	−0.003
	(0.499)	(0.500)	
Observations	6459	542	
Han ethnic	0.956	0.963	0.007
	(0.205)	(0.189)	
Observations	6459	542	
Urban *hukou*	0.807	0.817	0.01
	(0.395)	(0.387)	
Observations	6459	542	

This table compares the raw HSEE scores, CEE scores and demographic characteristics between included and excluded samples. The last column presents the difference of the variables and the significant level from *t*-statistics. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

Appendix B. Do Elite school and magnet class experience predict choice track

We use linear probability model to examine whether elite school and magnet class enrollment can affect student's choice between science and arts tracks. The dependent variable is a dummy, which equals to 1 if a student chooses a science track, or 0 if a student choose a arts track. We use [−0.1, 0.1] and [−0.3, 0.3] as the bandwidth. Table A2 reports the results. We find little evidence that the enrollment of elite school and magnet class can affect student's track choice.

Such finding is also consistent with intuition. The choice of science or arts track is an important issue for Chinese high school students. The points of comprehensive science or comprehensive social science accounts for 40% of the overall score of the CEE. Generally, the choice of track on students' innate ability and which track they are more skilled at.

Table A2
The effect of elite school/magnet class enrollment on track choice.

	Choice science track		Choice science track	
	[−0.1, 0.1]		[−0.3, 0.3]	
	(1)	(2)	(3)	(4)
Elite school enrollment	0.015	−0.037		
	(0.423)	(0.365)		
Magnet class enrollment			−0.003	−0.011
			(0.316)	(0.238)
Controls	Yes	Yes	Yes	Yes
Class by year effect	Yes	Yes	Yes	Yes
Observations	210	674	294	1039

This table presents results to test whether elite school and magnet class experience can predict students' choices between science and arts track. The dependent variable is a dummy, which equals to 1 if a student chooses science track and 0 if a student chooses arts track. We use linear probability model to regress this dummy variable on elite school/magnet class enrollment and students' characteristics, including gender, age, race and *hukou* registration status. We use [–0.1, 0.1] and [–0.3, 0.3] as the bandwidth. All regressions control class by year fixed effects. Standard deviations clustered at class level appear in parentheses. *, **, and *** represent the significant level at 10%, 5%, and 1% respectively.

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