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Are there educational and psychological benefits from private supplementary tutoring in Mainland China? Evidence from the China Education Panel Survey, 2013–15

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ABSTRACT

We investigate the educational and psychological benefits from participating in private supplementary tutoring in Mainland China. We use the 2013–2015 China Education Panel Survey data on junior high school students and a difference-in-difference and propensity score matching research design. Our results show that private tutoring is positively associated with higher English scores for rural students only. For all students and across most sub-groups, we find that private tutoring is associated with lower frequency of students' self-reported negative emotions. The data, however, do not permit deeper inquiry into the role of the quality and quantity of private tutoring.

1. Introduction

Exceedingly competitive education systems have contributed to the growth of after-school private tutoring in East Asian countries, especially in China, South Korea and Japan (Bray et al., 2014; Dang and Rogers, 2008; Li and Hu, 2017; Liu and Bray, 2018; Open Society Institute, 2006; Xu, 2015; Zhang and Bray, 2015, 2018). In China, many parents use private supplementary tutoring as a "fast lane" to help their children achieve social mobility, resulting in a large and growing private tutoring market. According to a 2016 survey conducted by the non-profit China Education Association for International Exchange (2017), the size of China's private supplementary tutoring market exceeded ¥800 billion (approximately $130 billion), with more than 137 million students having attended private supplementary tutoring. According to a 2014 nationwide survey, 29.8 % of Chinese primary and lower secondary students received private supplementary tutoring (Liu and Bray, 2018).

Private supplemental tutoring (henceforth, private tutoring) in China has attracted broad attention from the government, policy makers and researchers. Their concerns is that it affects not only the daily life of students but also families' education expenditures that may contribute to social stratification (Bray et al., 2014; Zhang, 2013). Studies from China find typically conclude that students from richer families receive more tutoring opportunities, and that private tutoring opportunities are more available to students from developed regions, higher quality schools, and urban families (Liu, 2014; Xue and Ding, 2009). The findings on whether private tutoring improves students' academic performance in China and elsewhere vary depending on the richness of the private tutoring measure, sample representativeness, and methodology (Byun, 2014; Dang, 2007; Kenayathulla, 2013; Li and Hu, 2017; Ryu and Kang, 2013; Zhang, 2013).

We contribute to the literature on private tutoring in Mainland China by addressing three questions. First, does private tutoring lead to educational benefits in Mainland China? Second, in addition to improving academic performance, are there any other benefits for students pursuing private tutoring? Third, how do the educational and psychological benefits from private tutoring vary across student gender, regional, and socioeconomic sub-groups?

To our knowledge, this study is the first to use national-level panel data to investigate the benefits of private tutoring. We use 2013–2014 data and the follow-up 2014–2015 data from the China Education Panel Survey (CEPS), a nationally representative survey involving approximately 20,000 junior high school students. We consider the utility of private tutoring in academic achievement to be a kind of *educational benefit* because many parents use it to help their children achieve success in school and high-stakes examinations. We measure its educational benefits using outcomes in the academic subjects that correspond to the examinations: Chinese, mathematics, and English. At the same

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time, we wonder if private tutoring also offers a form of *psychological benefit* that help parents and students relieve the stress and tensions created by a highly competitive education system. We measure the psychological benefits of private tutoring by using students' self-reported emotional wellbeing: mood, happiness, and life satisfaction.

The panel nature of the CEPS data permit us to use a difference-in-difference (DID) and propensity score matching (PSM) research design proposed by the Nobel Laureate James Heckman and his colleagues (Heckman et al., 1997, 1998). As we discuss later, this particular non-experimental method has several advantages over traditional methods (such as ordinary least squares with cross-sectional data).

Overall, our empirical analysis comparing private tutoring participants and non-participants in China shows that, on average, students participating in private tutoring may not have better educational outcomes but do report better psychological outcomes. Our results also suggest that the benefits from private tutoring vary by sub-groups: student gender, region, and socioeconomic status. We discuss possible policy implications and propose research possibilities with richer data on private tutoring and psychological outcomes.

2. Literature review and the Chinese context

2.1. Educational benefits: Human capital investment and educational competition

In seminal writings on human capital theory, Schultz (1961, 1980) and Becker (1960) considered the process of child cultivation to be the accumulation of human capital and emphasized the role of educational investment in the formation of human capital. The demand for private tutoring by Chinese families is a reflection of Schultz and Becker's human capital theory; i.e., private tutoring can help students succeed in a competitive educational system and ultimately change their economic fate. In addition, students who receive private tutoring can obtain other information about external academic resources, universities, and future careers from private tutors and tutoring institutions (Zhang and Bray, 2018).

The presence of private tutoring alongside the Chinese educational system provides can, in part, be explained by the standard micro-economic theory of supply and demand. This theory points out that public schools may reach their capacity limit, thus preventing them from offering as much education—in terms of both quantity and quality—as parents or students want. Private tutoring, as opposed to public education, can meet students' and parents' demand for education and encourage households to consume more education than they would through formal education only.

The Chinese educational system can be divided into compulsory education and postcompulsory education. Compulsory education is basically free, with the aim of providing universal education to students from different socioeconomic backgrounds. Postcompulsory education is not free, and there are approximately 2300 universities in China; however, only 112 are classified as "211 Projects," meaning they are elite universities that receive more financial support from the government than other regular universities. To receive an education in the elite universities, students must obtain excellent scores on the college entrance exam, which consequently inspires Chinese families' heavy investment in the compulsory education of their children (Xue and Ding, 2008; Yu and Ding, 2011; Zhang et al., 2011).

The quality of compulsory educational services the government provides to all children varies, in part, due to the "key school" system. China's compulsory education law stipulates that the distinction between key and non-key schools (or classes) is prohibited, and local governments can impose sanctions according to the law (2006 National People's Congress). In reality, however, the key schools continue to surpass ordinary schools in terms of reputation and resources (Yu and Ding, 2011). There is a general consensus and popular perception that entering a key high school is associated with a greater probability of recruitment by the elite universities, which in turn leads to higher social status (Shen, 2008; Zhang et al., 2011).

In view of the uneven development of compulsory education in various regions, the government began to implement the "nearby enrollment" policy to limit families' ability to mobilize to choose the best schools for their children (Li, 2007; Wu, 2008). As a result, purchasing a house in school district with key schools has become the most direct but also the most difficult educational investment because of the high price and the restrictions imposed by the household registration system. But even if a socioeconomically advantaged family buys a house in a district with a key school, the children in the family must still compete for limited educational opportunities in that area. Thus, families of all socioeconomic status considered private tutoring as a way of enhancing their children's human capital and increasing their competitiveness in school and high-stakes entrance examinations.

2.2. Psychological benefits: collective anxiety

In the past three decades, Chinese families have undergone vast changes in terms of status and social values because of the One-Child Policy. The only child has become the "only hope," the center and the future of the family (Fong, 2004; Lei and Chung, 2003). Parents use educational investments as a way to promote their children's human capital and success in education. Additionally, because of the rapid growth of the Chinese economy, the amount of economic resources that families have to invest in their children has been increasing (Lei and Chung, 2003; Shen and Du, 2009).

This attention and pressure has had consequences for the psychological wellbeing of both parents and children. On the basis of emerging reports (Liu, 2014; The Economist, 2018), we suspect that private tutoring may have emotional benefit, as widespread educational competition has caused collective anxiety in Chinese society. Many parents, especially low- and middle-income parents, experience a common struggle with regard to private tutoring: on the one hand, they have a vigilant mentality because private tutoring represents a substantial expense and increases the burden on students; on the other hand, they may seek support and comfort from private tutoring.

But several studies have shown that the pressure for Chinese students to participate in private tutoring is greater among students from higher-income backgrounds, as proxied by high academic achievement and higher ranking schools (Ma, 2011; Peng, 2008; Shen, 2008). In addition, students with high socioeconomic status and those from developed regions were more willing to accept private tutoring because of the more intense competition they experience. In addition, tutoring services are more plentiful and diverse for these students (Ma, 2011; Tsang et al., 2010). This collective anxiety implies that the entire society is worried about the solidification of class; and that educational investment in children has become a way to solve the "status panic".

The Chinese government has recognized the above issues and has been attempting to reduce the burden of exam-centered education on students (Zhang and Bray, 2015). The government has taken measures such as shortening class times and reducing the frequency of homework and exams. These policies were implemented based on good intentions, but they may have increased the pressure on and anxiety of parents and students. In turn, this increased families' demand for private tutoring because parents believed that it is more difficult for the school curriculum to meet the standards of the college and senior high school entrance examinations after the burden reduction efforts (Zhang and Bray, 2015); in other words, parents responded by compensating for this perceived gap through private tutoring.

2.3. Data and methodological limitations and possibilities

A common limitation of studies of private tutoring is that the samples are not probabilistic, and therefore inappropriate for making generalizations about the population. For example, studies that use

Programme for International Student Assessment (PISA) data for Shanghai fall into this category. It is also common for studies to have methodological limitations that make it difficult to establish causal relationships between participation in private tutoring and student outcomes. Since private tutoring opportunities are not randomly assigned, a simple comparison of the average educational and psychological outcomes of private tutoring participants and non-participants will lead to biased estimates of the treatment effects from private tutoring. Identification of the causal effects of private tutoring on student achievement is difficult because of data constraints and technical problems such as endogeneity. This means participation in private tutoring may be partially determined by exogenous variables that also determine the dependent variable (Zhang, 2013).

Some studies of private tutoring and academic achievement, such as those using ordinary least squares, do not take measures to control possible endogeneity problems. These findings, understandably, have been mixed. For instance, some compelling results were found in Vietnam (Kim and Lee, 2010) and Taiwan (Liu, 2012); but elsewhere, some harmful effects were found in Singapore (Cheo and Quah, 2005) and Korea (Lee et al., 2004). Ordinary least squares methods, however, cannot account for the unobserved differences between control and treatment groups such as parental motivation and student intelligence. These differences can affect dependent variables such as students' academic achievement, resulting in endogeneity problems that can make it difficult to obtain reliable causal inference.

Generally, instrumental variables are reliable methods for solving the above endogeneity problems in cross-sectional data. However, it is quite difficult to find an instrument that is strongly related to endogenous variables but not related to heterogeneous residual values. For example, Kang (2007) used student's birth order as an instrument to identify the effect of private tutoring costs on student outcomes. He assumed that parents had different educational investments for different children. But this instrument influences students' academic performance through other channels (such as the educational benefits from helping younger siblings with homework), leading to an overestimation of the effect of private tutoring. If parents have a particular preference for one child in terms of private tutoring investment, they will also prefer this child in other investments.

Dang (2007) used tutoring fees charged by schools in the commune as an instrument for private tutoring expenditures, and found that tutoring fees had a significant positive effect on student performance in Vietnam. This official hourly tutoring fee, however, is closely related to the socioeconomic status of the student's family, which is also a key variable affecting students' performance. Zhang (2013) used the distance between the student's home and the nearest tutoring institution and the number of participants in the student's peer group as instruments, but she acknowledged that these two variables can solve the endogenous problems only at the individual level, not at the macro environmental and institutional levels, because they are both individual variables at the student level.

Another way to solve the endogeneity problem of cross-sectional data is the matching method. Xu (2015) used the propensity score matching (PSM) method to estimate the impact of private tutoring on student achievement and found that it had a positive effect on students' mathematics scores but no effects on Chinese scores after controlling for other variables at the individual, family and school levels. Byun (2014) also employed the PSM technique to control for the pre-existing difference between Korean students who used a particular type of private tutoring and those who did not. The author found that most forms of private tutoring were not beneficial with the exception of a particular type called "preparatory cram school", which made a small difference in achievement gains in math. Hu et al. (2015) used reweighted PSM based on the PISA-Shanghai (2012) data of 15-year-old students and found that mathematics and science private tutoring had a positive effect on students' mathematics scores, while language private tutoring had a negative effect. However, PSM can solve the problem only of observable heterogeneity; it has no effect on unobservable heterogeneity. In addition, PSM using cross-sectional data cannot solve the problem of reverse causality. Many studies have shown that students' current academic performance heavily influences the probability that the students will participate in private tutoring in the future (Li, 2018; Xue and Ding, 2009), so private tutoring and academic achievement may be mutually causal.

Since reliable panel data are quite difficult to obtain, most research focusing on China has been based on cross-sectional data, and it is difficult to control for endogeneity problems in these data. The difference-in-difference (DID) technique may be better suited for use with panel data to address the issues of unobservable heterogeneity and reverse causality. Heckman and co-authors (1997, 1998) proposed combining a difference-in-difference (DID) technique with a PSM technique in order to overcome the influence of both unobserved variables and observable variables in the sample selection.

In sum, data and methodological issues make it difficult to make generalizations about the effect of private tutoring on student outcomes. Our study attempts to explore the impact of private tutoring on junior high school students' educational and self-reported psychological outcomes in Mainland China. This study extends beyond existing studies on the same topic in the following ways:

(a) It is the first study in China to use national-level panel data, which means the conclusions can be applied at the national level.
(b) It uses the PSM method jointly with DID analysis to control the observable and unobservable heterogeneity problems simultaneously, which makes the estimation more rigorous and reliable.
(c) It employs several measures of academic performance (instead of one or two measures, as in the existing literature) to improve the robustness of the findings.
(d) It is the first study in China to examine the impact of private tutoring on students' psychological state.

3. Data

3.1. The China Education Panel Survey (CEPS)

Our data are obtained from the CEPS, a national representative survey involving approximately 20 000 junior high school students. The first wave of data was collected in 2013–2014, with a follow-up investigation in 2014–2015. The survey employed a multistage probability proportionate to size sampling method, using first-year junior high school (grade 7) and third-year junior high school (grade 9) groups as the starting point of the survey. It used the average education level of the population and the proportion of the floating population as stratified variables. Twenty-eight county-level units were randomly selected as survey points in the country. The survey implementation took place in schools. At the selected county-level units, 112 schools were randomly selected, 438 classes were surveyed, and all students in the classes were sampled. The baseline survey included a total of approximately 20 000 students.

The follow-up investigation tracked 10,279 students in grade 8 (they were in grade 7 at the time of baseline survey). The number of students who were successfully followed was 9,449, the follow-up rate was 91.9 %, and the number of students who were lost to follow-up was 830. The main reasons for lack of follow-up data included transferring to other schools (589), dropping out (121) and other reasons (120). The CEPS contains widespread information on individual-, household-, and school-level characteristics. These are consistent with the needs of this study; the conclusions can be inferred at the national level. The sample for this study is 6808 after excluding samples with defects on important variables.

3.2. Outcome variables

To examine educational benefit, we use objective and subjective measures of student academic performance. The CEPS collected mid-term exam scores for students in the fall semester of 2014, and these were provided by schools. We standardize the scores based on classes, and the formula is as follows: standard score = (student score-class minimum score)/(class maximum score- class minimum score). Accordingly, we obtain the standard scores for Chinese, mathematics and English. Then, we aggregate the three scores to obtain the total standard score for each student.

We also use parents' assessment of their children's grades in the class as another operational indicator of academic performance. The CEPS asked parents "How does this child's academic record rank in his/her class at present?" The options included near the bottom = 1; below the average = 2; about the average = 3; above the average = 4; around the top = 5. To obtain a more robust and reliable estimate, we also use self-assessed learning difficulty in the three main subjects, Chinese, mathematics and English, as the dependent variable for the robustness test. The CEPS asked students three questions as follows: "At present, are the following courses difficult for you?" The sub-questions were Chinese, mathematics and English, and the options were 1 = not difficult at all, 2 = not very difficult, 3 = a bit difficult, and 4 = very difficult.

Finally, the emotional benefit is captured using the CEPS question: "Have you had the following feelings in the past seven days?" The sub questions included feeling blue, feeling unhappy, not enjoying life and feeling sad, and the options were 1 = never, 2 = seldom, 3 = sometimes, 4 = often, and 5 = always. Given that we are dealing with adolescents whose emotions and feelings oscillate significantly due to many factors, we would have benefitted from more objective indicators. Regrettably, the CEPS do not contain objective and stable measures of psychological state, including emotional well-being.[1] Without better measures, there is the possibility that students are giving responses that will please their parents.

An overall shortcoming of the CEPS 2013-15 is that the short nature of the panel data only permits us to examine the short-term effects of private tutoring. Consequently, we are unable to address the medium- and long-term benefits from participation in private tutoring during junior high school.

3.3. Independent variables

Our key independent variable is whether a respondent is enrolled in private tutoring for the three main subjects of Chinese, mathematics and English. The CEPS asked respondent four questions: "Which tutoring classes did you participate in? (1) Chinese/Chinese composition; (2) ordinary mathematics (does not include Olympic mathematics); (3) English; (4) any of the above." The answers were yes = 1, no = 0. Unfortunately, the CEPS does not include additional questions on the quality and quantity of the private tutoring services. For example, one-to-one tutoring is different from lecture-theater tutoring. Furthermore, holding other factors constant, the effectiveness of a single session per week is likely to be weaker than daily sessions. Finally, the identity and skills of the tutors as well as the abilities and motivations of students will affect the effectiveness of private tutoring sessions.[2]

We consider the following student, school and family covariate variables: gender (male = 1, female = 0); boarding (yes = 1, no = 0); ethnicity (Han = 1, other = 0); hukou (rural hukou = 0, urban hukou = 1); public school (yes = 1, no = 0); school location (city/town = 1, rural areas = 0); financial condition of family (very poor = 1, somewhat poor = 2, moderate = 3, somewhat rich = 4, very rich = 5); per capita funding level (0–25 % = 1; 25 %–50 % = 2; 50 %–75 % = 3; 75 %–100 % = 4); parent" years of schooling (none = 0; elementary school = 6; junior high school = 9; vocational/high school = 12; junior college = 15; bachelor's = 16; master's or higher = 19); parent's occupation type (elite = 1, non-elite = 0). We use the information from either the father or the mother; whichever is higher, when measuring parent's years of schooling and occupation type.

Table 1 shows the summary statistics. In general, we find that 48.5 % of students have participated in private tutoring for at least one subject. The private tutoring participation rates in Math (23.4 %) and English (26.1 %) are considerably higher than private tutoring participation in English (12.2 %). In comparing participants (T = 1) and non-participants (T = 0), we find comparable academic outcomes. In contrast, the psychological outcomes of non-participants are slightly better than those of participants.

4. Methods

4.1. Difference in difference model (DID)

The DID model is a commonly used method in policy evaluation (Heckman et al., 1997, 1998). The method divides the sample into intervention and control groups; the results for the control group are used as the counterfactual results for the intervention group. That is, the results of the control group are used to replace the results for the intervention group without being influenced by some kind of treatment and are then calculated. The difference between the results for the treatment group and the control group is calculated. An advantage of the DID method is that panel data can be used to control the effects of unobservable variables; specifically, the effects of time-invariant and time-varying changes can be controlled (Wan and Li, 2013).

The treatment group in this study includes students in the sample who attended private tutoring; the control group includes students in the sample who did not participate in private tutoring. The student outcomes for the control group are used as the counterfactual result of the student outcomes for the intervention group; we then calculate the difference between the factual result and the counterfactual result for the outcomes of the students in the treatment group and consequently obtain the effects of private tutoring on student outcomes, which is the average treatment effect on the treated (ATT). We provide the relevant equations in the Appendix section.

4.2. Propensity score matching (PSM)

The DID model must satisfy strict preconditions. One precondition is the assumption of random sample selection, and the other is the common trend assumption. However, students who accept private tutoring have differences in personal, family and school characteristics that are not randomly assigned. Therefore, simply treating the student outcomes of the control group as the counterfactual results of the student outcomes of the treatment group will cause sample selection bias. Before performing the double difference, a sample with similar characteristics to the treatment group should be selected as the control group.

To overcome the effects of causal inferences caused by endogeneity problems such as selection bias, we use PSM to match the intervention group to the control group before assessing the impacts of private tutoring on student outcomes (Guo and Fraser, 2010). PSM is a kind of causal inference method that is especially useful for controlling selection bias. Based on the counterfactual framework, PSM can create an intervention group with a distribution very close to that of the counterfactual (control) group on observable covariates. The propensity score is the probability that a unit falls into the intervention group under the condition of the given observable covariate. The researcher can achieve "balance" by matching the members of the intervention group with similar members of the control group according to the estimated propensity score. The matched sample satisfies the conditional independent

[1] We thank an anonymous referee for raising these points related to the limitations of such self-reported data on well-being.

[2] We thank two anonymous referees for raising these points related to the quality and quantity of private tutoring.

Table 1
Descriptive statistics for the variables.

Variables			N	Mean	SD	Minimum	Maximum
Independent variables		PT participation for any subjects	6808	0.4852	0.4998	0	1
		Math PT participation	6808	0.2337	0.4232	0	1
		Chinese PT participation	6808	0.1222	0.3276	0	1
		English PT participation	6808	0.2609	0.4391	0	1
Dependent variables	T = 0	Parent-rate ranking	6808	3.1661	1.0270	1	5
		Standard total score	6808	0.6705	0.2060	0	1
		Standard math score	6808	0.6596	0.2576	0	1
		Standard Chinese score	6808	0.6538	0.2238	0	1
		Standard English score	6808	0.6980	0.2550	0	1
		Self-assessed learning difficulty in math	6808	2.4634	0.9063	1	4
		Self-assessed learning difficulty in Chinese	6808	2.7288	0.7877	1	4
		Self-assessed learning difficulty in English	6808	2.6062	0.9592	1	4
		Feeling blue	6808	2.1576	0.9533	1	5
		Feeling unhappy	6808	2.2081	1.0056	1	5
		Not enjoying life	6808	1.6561	1.0134	1	5
		Feeling sad	6808	1.9802	0.9976	1	5
	T = 1	Parent-rate ranking	6808	3.1535	1.0470	1	5
		Standard total score	6808	0.6410	0.2229	0	1
		Standard math score	6808	0.6416	0.2776	0	1
		Standard Chinese score	6808	0.6651	0.2248	0	1
		Standard English score	6808	0.6162	0.2799	0	1
		Self-assessed learning difficulty in math	6808	2.5198	0.8714	1	4
		Self-assessed learning difficulty in Chinese	6808	2.8638	0.7504	1	4
		Self-assessed learning difficulty in English	6808	2.3995	0.9831	1	4
		Feeling blue	6808	2.3001	1.0477	1	5
		Feeling unhappy	6808	2.2828	1.0577	1	5
		Not enjoy life	6808	1.8988	1.0934	1	5
		Feeling sad	6808	2.0958	1.0527	1	5
Covariates		Gender	6808	0.5116	0.4999	0	1
		Boarding	6808	0.2991	0.4579	0	1
		Ethnicity	6808	0.0736	0.2611	0	1
		Hukou	6808	0.5073	0.5000	0	1
		Financial condition of family	6808	0.8575	0.4869	0	2
		Parents' years of schooling	6808	10.7854	3.1431	0	19
		Parents' occupation type	6808	0.2522	0.4343	0	1
		Public school	6808	0.9385	0.2403	0	1
		School location	6808	0.3327	0.4712	0	1
		Per capita funding level	6808	2.0091	1.2457	1	4

distribution hypothesis, and the average treatment effect (ATE) can be obtained by comparing the average difference of the dependent variables between the intervention group and the control group in the final match. The relevant equations are included in the Appendix section.

4.3. The PSM-DID method

Although the PSM method can overcome the sample selection bias of observable variables, it can match only two sets of samples based on observable variables. In other words, the method assumes that the acceptance of private tutoring is entirely dependent on observable variables and that the unobserved variables (such as student ability) have no effect. Therefore, PSM cannot correct the impact of unobserved variables on whether students attend private tutoring, and the ATE estimated using the PSM method is still biased. The double difference method can overcome the influence of unobservable variables, and it can be a well-fitted solution to compensate for the deficiency of the PSM method in this respect. For this reason, Heckman et al. (1997,1998) proposed the joint PSM-DID method, which can fully utilize the advantages of the DID and PSM methods and overcome the influence of unobserved variables and observable variables on sample selection. Accordingly, we adopt the joint PSM-DID method to control the impact of unobserved and observable variables on students' acceptance of private tutoring, effectively resolving the problem of sample selection bias and thus obtaining the average ATT of private tutoring on students' outcomes. The equations are included in the Appendix section.

A key shortcoming of the PSM-DID method is that it cannot control the heterogeneity problem over time, such as changes in student motivation and the availability of tutoring services. Although we controlled the variables that changed over time as much as possible and minimized the time span of the data, we still could not entirely address the endogeneity problems described above. This shortcoming undermines our ability to make causal statements.

5. Results

5.1. Private tutoring on academic outcomes

Based on a balance test and common support test, the matched samples satisfied the premises of the PSM-DID method (including the conditional independent distribution hypothesis and the common support hypothesis).[3] We use the standard scores for Chinese, mathematics

[3] We first establish a propensity score model to predict whether students will attend private tutoring for Chinese, mathematics, English or any combination of these subjects. The results are shown in Appendix Table A1. The data show that the four regression results from the logit model before matching are well fitted. Specifically, when the dependent variable is private tutoring for any subjects, the model's values are LRchi2 = 1153.55, p = 0.000, pseudo R^2 = 0.1223. When the dependent variable is private tutoring for mathematics, the model's values are LRchi2 = 495.14, p = 0.000, pseudo R^2 = 0.0669. When the dependent variable is private tutoring for Chinese, the model's values are LRchi2 = 180.83, p = 0.000, pseudo R^2 = 0.0358. Finally, when the dependent variable is private tutoring for English, the model's values are LRchi2 = 812.58, p = 0.000, Pseudo R^2 = 0.1040.

Table 2
PSM-DID results: The effect of private tutoring on students' academic performance.

	Grade 7			Grade 8			PSM DID
	Control group	Treatment group	Difference	Control group	Treatment group	Difference	
Parent-rate ranking	3.110	3.143	0.033	3.110	3.138	0.028	−0.005
Standard error			0.030			0.029	0.023
t-value			1.08			0.97	0.22
p > |t|			0.283			0.22	0.828
R^2							0.00
Standard total score	0.652	0.666	0.014	0.624	0.628	0.004	−0.009
Standard error			0.006			0.007	0.005
t-value			2.13			0.66	1.87
p > |t|			0.034**			0.508	0.062*
R^2							0.01
Standard math score	0.652	0.648	−0.004	0.641	0.647	0.006	0.010
Standard error			0.011			0.011	0.011
t-value			−0.40			0.52	0.96
p > |t|			0.687			0.600	0.340
R^2							0.00
Standard Chinese score	0.653	0.647	−0.006	0.665	0.667	0.002	0.008
Standard error			0.011			0.012	0.010
t-value			−0.55			0.14	0.76
p > |t|			0.585			0.888	0.446
R^2							0.00
Standard English score	0.710	0.746	0.037	0.640	0.676	0.035	−0.001
Standard error			0.011			0.012	0.009
t-value			3.25			3.00	0.14
p > |t|			0.001***			0.003***	0.888
R^2							0.02

* p < 0.1.
** p < 0.05.
*** p < 0.01.

and English, the total score and the parent-rate ranking as the outcome variables to estimate the ATE of private tutoring on students' academic outcomes. The results from the PSM-DID method are presented in the last column of Table 2. According to the results in Table 2, private tutoring does not have a statistically significant association with parent-rate ranking, math score, and Chinese score. Specifically, participation in Chinese/mathematics/English private tutoring is associated with slightly higher standard scores for Chinese and mathematics and lower score for English, but all these associations are statistically insignificant. Curiously, private tutoring does have a statistically significant (at the 10 percent level of significance) and small negative association with the standard total score. In particular, students who participate in private tutoring score very slightly (0.009 standard deviations) below the mean, holding other observable factors and time-invariant unobservable factors constant.

To assess the robustness of the above findings, we use self-assessed learning difficulty in the three main subjects of Chinese, mathematics and English as outcome variables to test the robustness; students responses ranges from 1 ('not difficult at all) to to 4 ('very difficult'). As discussed earlier, self-assessed learning difficulty should reflect students' academic performance to a certain extent, so these variables can be used as proxy variables for academic achievement. The PSM-DID results are shown in the last column of Table 3. We find that participation in private tutoring for mathematics and English has no statistically significant association with self-assessed learning difficulty in these two subjects. Rather, participation in private tutoring for Chinese was statistically associated with 0.072 points greater self-assessed learning difficulty in Chinese; given that the self-assessed learning difficulty score range between 1 and 4, the 0.072 points difference is quite small. It is unclear if private tutoring makes students realize their weakness in Chinese, or if the tutoring is of such low quality that it harms their Chinese.

In summary, the PSM-DID analysis indicate that private tutoring is not positively associated with objective and subjective measures of academic performance. Rather, participation in private tutoring is statistically associated with greater self-assessed difficulty of learning in Chinese.

5.2. The effect of private tutoring on psychological outcomes

Table 4 shows the statistical associations between participating in private tutoring and students' self-reported psychological outcomes. As noted earlier, we consider four measures of emotion (feeling blue, feeling unhappy, not enjoying life, and feeling sad) with the outcomes taking on values between 1 ('never') and 5 ('always'). The statistically significant findings indicate that private tutoring is associated with slightly decreased frequency of negative psychological perceptions among junior high school students, holding other factors constant. In particular, private tutoring is negatively associated with feeling blue (0.061 points), not enjoying life (0.065 points), and feeling sad (0.085 points). The negative association between private tutoring and feeling unhappy (0.057 points) is also statistically significant but at the 10 percent level. In summary, participating in private tutoring is associated with better psychological health of junior high school students in mainland China.

5.3. Heterogeneity across different groups

To explore hetereogeneity of the statistical associations, we divide the total sample into eight subsamples according to gender, region, per capita funding level and parental occupation type. The PSM-DID results are shown across all columns in Table 5. In general, the results of suggest heterogeneity in the educational and psychological benefits from private tutoring.

Notably, private tutoring has a negative and statistically significant association with the total scores of students who are male and relatively disadvantaged backgrounds (that is, those who reside in rural areas and have parents with non-elite occupations). In contrast, private tutoring is positively and significantly associated with standard mathematics scores for the top 50 % of per capita funding and urban subsamples.

Table 3
PSM-DID results: The effect of private tutoring on students' self-assessed learning difficulty.

	Grade 7			Grade 8			PSM-DID
	Control group	Treatment group	Difference	Control group	Treatment group	Difference	
Self-assessed learning difficulty in math	2.509	2.541	0.032	2.582	2.632	0.050	0.017
Standard error			0.031			0.032	0.031
t-value			1.01			1.53	0.55
p > |t|			0.314			0.128	0.585
R^2							0.000
Self-assessed learning difficulty in Chinese	2.766	2.749	−0.017	2.897	2.952	0.055	0.072
Standard error			0.029			0.038	0.034
t-value			−0.58			1.45	2.11
p > |t|			0.564			0.150	0.036**
R^2							0.01
Self-assessed learning difficulty in English	2.649	2.869	0.220	2.519	2.722	0.203	−0.017
Standard error			0.037			0.035	0.033
t-value			5.90			5.74	0.50
p > |t|			0.000***			0.000***	0.616
R^2							0.02

*p < 0.1.
** p < 0.05.
*** p < 0.01.

These sets of results may reflect the higher quality of private tutoring that is available to those from richer backgrounds and urban areas. But it is unclear why male students who participate in private tutoring have lower scores than male students who do not participate.

Across the different groups, there are no cases of statistically significant associations between private tutoring and standard Chinese scores or math scores. For rural students, however, participation in private tutoring is associated with relatively large gains (0.036 points) in standard English scores; this may because private tutoring compensates for the low quality in formal English education in some areas of rural China.

In terms of psychological benefits, the subsample analyses reveal that positive and statistically significant associations mainly exist for male students and those from relatively disadvantaged backgrounds—students from rural areas, students in the bottom 50 % of per capita funding, and especially students whose parents had non-elite occupations).

Overall, we observe more cases of educational and psychological benefits from private tutoring for males and students from relatively disadvanted backgrounds (that is, those from rural areas, students in the bottom 50 % of per capita funding and students whose parents have non-elite occupations).

6. Conclusion and discussion

Based on panel data from the CEPS 2013-15, this study explored the impact of private tutoring on junior high school students' academic performance and found that private tutoring typically does not have

Table 4
PSM-DID results: The effect of private tutoring on students' self-reported emotions.

	Grade 7			Grade 8			PSM-DID
	Control group	Treatment group	Difference	Control group	Treatment group	Difference	
Feeling blue	2.170	2.197	0.027	2.322	2.288	−0.034	−0.061
Standard error			0.024			0.025	0.031
t-value			1.14			1.34	1.97
p > |t|			0.256			0.183	0.050**
R^2							0.00
Feeling unhappy	2.254	2.293	0.038	2.331	2.312	−0.019	−0.057
Standard error			0.023			0.027	0.031
t-value			1.68			0.69	1.81
p > |t|			0.095*			0.488	0.072*
R^2							0.00
Not enjoying life	1.656	1.750	0.094	1.925	1.954	0.029	−0.065
Standard error			0.025			0.025	0.029
t-value			3.83			1.15	2.29
p > |t|			0.000***			0.251	0.023**
R^2							0.01
Feeling sad	2.033	2.051	0.018	2.175	2.108	−0.067	−0.085
Standard error			0.025			0.025	0.029
t-value			0.74			2.69	2.98
p > |t|			0.462			0.008***	0.003***
R^2							0.00

* p < 0.1.
** p < 0.05.
*** p < 0.01.

Table 5
PSM-DID results: Heterogeneity of the effects of private tutoring among different groups.

Outcome variables	Gender		Region		Per capita funding level		Parent's occupation	
	Male	Female	Urban	Rural	The last 50 %	The top 50 %	Elite	Non-Elite
Parent-rate ranking	0.007	−0.018	0.034	−0.020	−0.006	0.004	−0.018	−0.001
	(0.034)	(0.032)	(0.034)	(0.033)	(0.034)	(0.031)	(0.054)	(0.026)
Standard total score	−0.013**	−0.004	−0.004	−0.011*	−0.006	−0.013**	−0.002	−0.010**
	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)	(0.005)	(0.009)	(0.005)
Standard math score	0.011	0.010	0.027*	−0.010	−0.012	0.029*	0.020	0.009
	(0.011)	(0.013)	(0.014)	(0.010)	(0.011)	(0.015)	(0.015)	(0.010)
Standard Chinese score	0.011	0.001	0.009	0.005	0.008	0.007	0.004	0.010
	(0.014)	(0.011)	(0.013)	(0.015)	(0.015)	(0.014)	(0.013)	(0.012)
Standard English score	−0.005	0.000	−0.017	0.036***	0.001	−0.002	−0.018	0.011
	(0.012)	(0.009)	(0.011)	(0.010)	(0.014)	(0.010)	(0.011)	(0.010)
Feeling blue	−0.075*	−0.015	−0.051	−0.070*	−0.093**	−0.033	0.010	−0.075**
	(0.041)	(0.042)	(0.040)	(0.039)	(0.044)	(0.043)	(0.057)	(0.033)
Feeling unhappy	−0.075	−0.041	−0.065	−0.057	−0.072	−0.053	−0.065	−0.071**
	(0.046)	(0.039)	(0.043)	(0.041)	(0.045)	(0.043)	(0.061)	(0.035)
Not enjoying life	−0.083**	−0.048	−0.088**	−0.065*	−0.084*	−0.070*	−0.076	−0.074**
	(0.041)	(0.039)	(0.044)	(0.037)	(0.043)	(0.039)	(0.062)	(0.032)
Feeling sad	−0.116***	−0.045	−0.018	−0.118***	−0.138***	−0.022	−0.065	−0.086***
	(0.042)	(0.040)	(0.041)	(0.038)	(0.041)	(0.041)	(0.056)	(0.032)

positive and statistically significant associations with standard scores for Chinese, mathematics or English or on parental ranking at the total sample level. Further, we explored the statistical associations between private tutoring and students' psychological state and found that private tutoring is negatively associated with emotions such as feeling blue, feeling unhappy, not enjoying life and feeling sad. The above findings for the total sample suggest that psychological benefits might be important factors driving students to participate in private tutoring in Mainland China.

Our analysis on the subsamples found that private tutoring is negatively associated with standard total scores for male students, students from rural areas, and students whose parents had a non-elite occupation. It is positively associated with standard math scores, however, for students in the top 50 % of per capita funding and urban subsamples. Thus, private tutoring may have educationally benefitted advantaged groups, but not disadvantaged groups. From this perspective, private tutoring may inadvertently enlarge inequality in academic achievement among different groups. We posit two possible reasons for differences across sub-groups. First, a reason for the possible educational ineffectiveness of the disadvantaged groups' private tutoring may be that the quality of tutoring is worse in rural areas, and among students with less per capita funding. Second, parents of disadvantaged groups are less educated and unable to identify whether private tutoring is educationally effective. In rural or economically underdeveloped areas of China, many parents have been working in distant cities for a long time and cannot accompany their children. All they can provide to their children is financial support instead of emotional support and academic guidance. Such families are more likely to feel pressure and be affected by the external environment.

We further explored the impact of private tutoring on psychological outcomes in different subsamples. We found statistically significant associations between private tutoring and emotional outcomes for male students and students from both advantaged and disadvantaged backgrounds. Our findings suggest, therefore, that regardless of the educational benefit students obtain through private tutoring, the emotional benefits might be driving them to participate in private tutoring.

Our findings have social and policy implications. As pointed out by Yu and Ding (2011), China's huge private tutoring industry may be influenced by the "herd behavior" of rational individuals under the pressure of educational competition. Parents may then choose private tutoring to cope with educational competition. When parents make educational choices for their children, they may be choosing the lesser of evils from a less-than-ideal array of options. It may be that many Chinese parents suspect tutoring has a minimal impact on their children's education. With limited alternatives, however, parents may be reluctant to pull their children from tutoring. We simply do not know. From a policy perspective, it may be difficult for the government to regulate the educational (in)effectiveness of certain private tutoring services. Indeed, a case study by Zhang and Bray (2018) showed that the private tutoring market operated in a space beyond governmental control.

Future research that combines the DID-PSM method with richer data may provide deeper insight into the educational and psychological benefits provided by private tutoring in China. For instance, with more detailed data on the quality and quantity of private tutoring, researchers could explore how the effectiveness of private tutoring can vary by tutor qualifications, peer quality, and the format of tutoring sessions. In addition, further insight into the emotional benefits derived from private tutoring could be explored using data that contain more objective measures of psychological well-being. Finally, additional rounds of the CEPS could permit inquiry into longer-term benefits (e.g., outcomes in college and the labor market) from participating in private tutoring during junior secondary level. Such research could provide a more compelling answer to whether private tutoring really is a "fast lane" to social mobility in China.

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Appendix A

Table A1
Result of the balance tests.

Covariate variables		PT participation for any subjects		Mathematics PT participation		Chinese PT participation		English PT participation	
		%bias	p > |t|	%bias	p > |t|	%bias	p > |t|	%bias	p > |t|
Gender	Unmatching	9.6	0.000	−6.1	0.034	3.4	0.361	−4.1	0.142
	Matching	−0.4	0.870	−0.5	0.895	1.4	0.782	0	1.000
Boarding	Unmatching	46.2	0.000	−40.8	0.000	−15	0.000	−48.9	0.000
	Matching	0.2	0.946	−1.9	0.546	−3.1	0.513	−2.8	0.323
Ethnicity	Unmatching	5.4	0.026	−7.8	0.008	−7.3	0.061	−5	0.078
	Matching	2.7	0.275	0.2	0.960	−0.9	0.845	−0.4	0.890
Hukou	Unmatching	55.3	0.000	−42.7	0.000	−28.9	0.000	−59	0.000
	Matching	−0.9	0.704	−1.7	0.617	−5.7	0.240	−0.5	0.872
Financial condition of family	Unmatching	−37.7	0.000	28.7	0.000	26.6	0.000	34.4	0.000
	Matching	−2	0.449	1.3	0.704	5.4	0.256	1.8	0.570
Parents' years of schooling	Unmatching	−65.8	0.000	46.5	0.000	41.7	0.000	63	0.000
	Matching	−0.5	0.822	2.7	0.471	8.5	0.096	0.6	0.869
Parents' occupation type	Unmatching	−52.4	0.000	34.5	0.000	33.1	0.000	47	0.000
	Matching	−1	0.612	2.4	0.526	6.5	0.210	−1.4	0.706
Public school	Unmatching	−8.5	0.000	4.5	0.124	2.4	0.517	15.4	0.000
	Matching	3.2	0.236	0.3	0.941	0.8	0.871	0.9	0.753
School location	Unmatching	56.2	0.000	−43.9	0.000	−29.8	0.000	−54.3	0.000
	Matching	1.7	0.524	−1.5	0.635	−5.1	0.271	−2.5	0.385
Per capita funding level	Unmatching	−35.3	0.000	34.5	0.000	18.8	0.000	27.8	0.000
	Matching	−2.4	0.283	1.8	0.636	4	0.431	−1.8	0.614
Pseudo R2	Unmatching	0.122		0.067		0.036		0.104	
	Matching	0.001		0.000		0.002		0.001	
LR chi2	Unmatching	1153.55		495.14		180.83		812.58	
	Matching	5.21		0.94		3.96		2.72	
P > chi2	Unmatching	0.000		0.000		0.000		0.000	
	Matching	0.877		1.000		0.949		0.987	

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ijedudev.2019.102144.

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