working paper
2013-03

The impact of a senior high school tuition relief program on poor junior high school students in rural China

Xinxin Chen
Yaojiang Shi
Hongmei Yi
Linxiu Zhang
Di Mo
James Chu
Prashant Loyalka
Scott Rozelle

June 2013

partnership for economic policy
pep

The Impact of a Senior High School Tuition Relief Program on Poor Junior High School Students in Rural China

Abstract

A significant gap remains between rural and urban students in the rate of admission to senior high school. One reason for this gap may be high tuition and other school fees at the senior high school level. By reducing student expectations of attending high school, high tuition and school fees can reduce student academic performance in junior high school. In this paper we evaluate the impact of a senior high tuition relief program on the test scores of poor, rural seventh grade students in China. We surveyed three counties in Shaanxi Province and exploit the fact that, while the counties are adjacent to one another and share similar characteristics, only one of the three implemented a tuition relief program. Using several alternative estimation strategies, including difference-in-differences (DD), difference-in-difference-in-differences (DDD), propensity score matching (PSM) and difference-in-differences matching (DDM), we find that the tuition program has a statistically significant and positive impact on the math scores of seventh grade students. More importantly, this program is shown to have the largest (and only significant) impact on the poorest students.

JEL codes: I22, O12, O15

Keywords: Tuition relief program, education program evaluation, rural China

Authors

Xinxin Chen*
Zhejiang Gongshang University
Hangzhou, China
Contact: chenxx@mail.zjgsu.edu.cn

Hongmei Yi and Linxiu Zhang
Center for Chinese Agricultural Policy,
Institute of Geographical Sciences and
Natural Resources Research,
Chinese Academy of Sciences
Beijing, China

Yaojiang Shi
Northwest Socioeconomic Development
Research Center, Northwest University
Xi'an, China

Di Mo
LICOS - Centre for Institutions and Economic
Performance, Katholic University of Leuven

James Chu, Prashant Loyalka and Scott Rozelle
Stanford University
Stanford (CA), United States

Acknowledgements

This research work was carried out with financial and scientific support from the Partnership for Economic Policy (PEP) with funding from the Australian Agency for International Development (AusAID), the Department for International Development (DFID) of the United Kingdom (or UK Aid), and the Government of Canada through the International Development Research Center (IDRC). www.pep-net.org

The authors would also like to acknowledge the support of LICOS, K.U. Leuven, and the grants from the National Natural Science Foundation of China (grant numbers 70803047 and 71273237). The project could not have been possible without the collaboration of the Ningshan County, Shiquan County and Hanyin County bureaus of education. In particular, the authors wish to thank Jiang Jun, the former head of Education Bureau of Ningshan, for his support during the project, as well as many students from Northwest University of Xi'an, most notably Fan Li and Huan Wang, who carried out the survey work.

Table of content

Introduction

After more than a decade of dedicated effort to universalize access to primary education, policymakers in developing countries are shifting their focus towards expanding access to secondary education (UNESCO, 2011). One major challenge that policymakers in developing countries face in expanding access to secondary education (junior and senior high school), however, is that students from rural areas are relatively underrepresented in senior high school (e.g. see Carneiro et al, 2011; Ohba, 2011). Since students from rural areas are less likely than students from urban areas to attend senior high school, they are less likely to benefit from the high economic returns associated with both senior high school and college (Psacharopoulos and Patrinos, 2004). The lack of access to senior high school among rural students may thus lead to greater income inequality between urban and rural areas as well as lower economic growth (Sala-i-Martin et al, 2004).

As in the rest of the world, low educational attainment in poor rural areas is an important and emerging issue in China. Students in most poor rural counties in China enrol in senior high school at a far lower rate than urban students (Yang, 2006). Nearly 90 percent of students in large cities in China attend senior high school. In rural areas, however, roughly just 1 in 4 students attend senior high school (Liu et al, 2009).

This gap in school participation presents a challenge for China's education system to meet its goals and may, in the longer run, harm the economy. In 2010, China's Ministry of Education set the goal of having all students complete 12 years of schooling (including primary, junior high and senior high education) by 2020 (Ministry of Education, 2010). While progress has been made in parts of the country, elevated junior high dropout rates (Mo et al, 2011) and low senior high school matriculation rates in poor rural areas (Yi et al, 2012) mean that educators face major challenges in meeting the goal of universal secondary education.

Lack of interest by poor rural students in attending senior high school also has implications for China's equitable development in the long run. When poor rural children end up working in factories or in construction sites to obtain short-run returns rather than studying math, language, English and computers, there is good reason to be concerned that children are not learning the skills that will be needed to be gainfully employed in China's future labour market (Rozelle et al, 2012). If China's economy continues to grow rapidly over the coming decade or more, wages, which have been rising fast in recent years (Cai, 2007), will almost certainly continue to increase. However, employers will only be willing/able to hire workers with skills that are worth high hourly rates. Workers that lack such skills will either be forced to find employment in the informal economy (where returns are low and expectations of future wage increases are limited) or will become unemployed (Deming, 2011). Hence, while rich urban students reap high returns, students from poor rural families might be left behind, leading to chronically high unemployment rates, embedded inequality and potentially even growth-reducing instability.

A major barrier preventing rural students from attending senior high school in many developing countries is high tuition fees. High tuition fees are an obvious problem because poor rural families have limited resources to pay for tuition and other direct costs of education (Banerjee et al, 2000). These poor rural families may also be unable to borrow money to pay tuition fees due to limited access to well-functioning credit markets (Banerjee, 2004). Where well-functioning credit markets do exist, market imperfections may still prevent families from borrowing money, such as difficulties using human capital to serve as collateral for educational loans (Deininger et al, 2003; Jacoby, 1994). Even when families can get their hands on the funds to pay tuition fees, the opportunity cost of going to school can make the total cost of schooling prohibitively expensive (Lincove, 2012; Angrist and Lavy, 2009; Angrist et al, 2002).

In a context of high tuition fees, the highly competitive nature of education systems in many developing countries can further prevent poor, rural students from attaining higher levels of schooling (Glewwe and Kremer, 2006). Educational systems in developing countries (such as China) often use competitive entrance exams to allocate limited positions in schools. Poor rural students have lower average scores on standardized tests (Sirin, 2005; White, 1982) and thus may fail to qualify for higher levels of schooling. Poor rural students may also perceive that they will have fewer opportunities to qualify for higher levels of schooling or to enter more selective schools, and thus may be discouraged from staying in school long before they reach the stage of taking entrance exams (Chuang, 1997; Reardon and Galindo, 2002; Valenzuela, 2000). Since schools in these competitive education systems are often incentivized based on their exam results, schools and teachers may further push at-risk poor students to drop out in an effort to raise overall test scores (Velez and Saenz, 2001). In general, when educational systems allow schools to select students on the basis of ability and where there is competition between schools, poor students are more likely to attend lower quality schools, reduce effort, and complete fewer years of schooling (MacLeod and Urquiola, 2009).

High tuition fees and a competitive entrance exam system appear to be major reasons behind the low senior high school matriculation rates among students from poor rural areas in China. Most notably, rural public senior high schools in China still charge some of the highest tuition fees in the developing world and are often unaffordable for students from poor rural areas (Liu et al, 2009). Not only are tuition fees high, but students from poor rural areas appearing to overestimate the actual costs of attending senior high school (Loyalka et al, 2010). A perception of high tuition fees along with the rigors of China's competitive education system may also discourage students from poor rural areas from exerting effort to learn in junior high school, thus lowering their chances of attending senior high school (Yi et al, 2012; Wang et al, 2011).

In China, senior high school is non-compulsory and tuition (at least until recently) is almost fully paid for by the family. Expensive tuition may lead poor families and students to decide not to go to senior high school (Liu et al, 2009). Indeed, the cost of sending a student to senior high school is several times the per capita annual income of a poor rural family. For example, in poor rural areas in Shaanxi Province, annual per capita income was only 2,400 yuan (US$381) in 2008 (Ankang Statistics Bureau, 2009). However, senior high school tuition and fees averaged 8,000 yuan (US$1270) per year—more than 3 times the annual per capita income of a poor family. Moreover, higher wages mean that the opportunity cost of going to senior high school has increased, given the assumption that a student attending high school cannot work or otherwise earn an income for his or her family. The typical unskilled worker earns more than 11,000 yuan (US$1746) per year (Huang et al, 2011), so the opportunity cost is more than double the direct (cash) costs of going to senior high school. Waiving tuition is thus a promising way to increase enrolment rates. Indeed, since tuition was waived for primary and junior high students, the junior high school enrolment rate in rural China has increased significantly (Ministry of Education, 2009).

The overall goal of this paper is to evaluate the effectiveness of a senior high school tuition relief program in promoting education in poor rural areas and in encouraging students to exert more effort in preparing for senior high school. More precisely, we are interested in knowing whether students will respond to the tuition reduction program by (working harder and) performing better if a school district offers tuition relief and informs junior high school students of this fact.

To accomplish this goal, we draw on the fact that one poor county in southern Shaanxi Province—Ningshan County—implemented a senior high school tuition relief program. Two neighbouring (and quite similar) counties—Shiquan and Hanyin—did not implement any tuition relief programs. Hence, we believe that this arrangement can serve as a quasi experiment, allowing us to evaluate the impact of Ningshan's senior high tuition relief program on the academic achievement of poor rural seventh grade students. To address our concerns that this does not constitute a randomized and controlled trial (although Ningshan is similar to Shiquan and Hanyin, there may be differences other than the tuition relief program), we conduct difference-in-differences (DD) estimation, difference-in-difference-in-differences (DDD) estimation, propensity score matching (PSM) and difference-in-differences matching (DDM). Above all, we are interested in examining whether the impact differs between the poorest and richest students. In other words, we also investigate whether this program has a more of an impact on the poorest students, whose families are more likely to be liquidity constrained.

In seeking to achieve such an ambitious goal, we also acknowledge certain limits. By the time of the endline survey in September 2010, the first cohort of students that could enjoy the benefits of the Ningshan tuition relief program, which officially started in September 2009, had only completed their first year of junior high school. Because of this, we are unable to quantify the impact of the program on the number of students actually continuing on to high school as a result of the program. Indeed, at present we can only evaluate the effect of the tuition relief program on the effort of first year junior high school students, or more precisely, on their performance on two standardized math tests developed and executed by the research team (one conducted before the start of the tuition relief program in September 2009 and the other conducted one year later in September 2010). We are also aware that this quasi experiment only covers three counties in poor areas of rural China. There are hundreds of poor rural counties in other parts of China. We believe that our work can inform the debate of whether tuition relief should be offered in these counties, but we do not claim full external validity for other poor areas.

The rest of the paper is organized as follows. The first section introduces the tuition relief program, followed by our data collection and sampling methodology. We then describe our analytic approach. Finally, we present the results of the study and discuss their implications.

Ningshan County's Tuition Relief Program

A tuition relief program implemented in the Ningshan County provides us with an opportunity to examine the effect of such programs on the academic performance of junior high students in China's poor rural areas. Ningshan is a nationally designated poor county that is rural, where 2009 per capita income was 3201 yuan (US$ 500).

Like in other rural areas, the annual costs of attending senior high school far exceed the income of poor families. According to an official website administered by the Ankang Prefecture Bureau of Education, senior high school tuition in 2010 was 1500 yuan (US$238) per year[1] plus other fees and miscellaneous expenses. In interviews with officials in Ningshan, Shiquan and Hanyin, we were told that about 80 percent of senior high students lived in dormitories on campus. According to a survey of senior high school students elsewhere in Shaanxi Province, senior high students had to pay an average of an additional 8000 yuan (US$1270) per year for accommodation, food, and learning materials (Liu et al, 2010).

The Ningshan tuition relief program was announced at the end of July in 2009 during summer vacation. The local government promised to pay annual tuition of 1500 yuan

[1] All the counties studied in this paper (Ningshan, Shiquan and Hanyin) are located in the same prefecture (Ankang) in Shaanxi Province.

(about US$238) per year for three years for senior high school students who were among the top 500 students in the senior high school entrance exam. The average annual enrolment of 550 in the only senior high school in this county means that the program coverage was 91 percent. In effect, the program meant that most students enrolling after August 2009 did not need to pay tuition.

Moreover, all junior high students were informed of the tuition relief program. Although only 15% of junior high students knew about the program in September 2009, when we revisited the schools in March 2010, 100 percent of the students that we randomly selected from grade 7 (or the first year of junior high school) were aware of the program and could generally describe the nature of the program. According to interviews with officials in the bureau of education, the government conducted an intensive promotional effort to make this program known to all junior high students in early October 2009. Hence, if the program has any effect, it could possibly be appearing as early as grade 7.

The neighbouring counties of Shiquan and Hanyin are located in the same prefecture as Ningshan. In each prefecture in China, students are usually required to take the same courses, use the same textbooks, take the same senior high school entrance exams and pay the same amount of tuition. This holds true in the Ankang Prefecture.

There were other similarities between Ningshan and Shiquan/Hanyin counties. Like Ningshan, the Shiquan and Hanyin counties are nationally- or provincially-designated poor counties.[2] In 2009, rural per capita income was 3323 yuan (US$519) in Hanyin and 3338 yuan (US$522) in Shiquan. All three counties are extremely mountainous. Per capita fiscal revenues are nearly zero in all three counties, meaning that almost all educational expenditures are financed by transfers from prefecture, province and national level governments. Moreover, more than 98 percent of the rural populations in all three counties are Han. We can thus say that the three countries are nearly identical

[2] In 1994, China's government launched a poverty-reduction initiative under the "8-7 Plan" and defined 592 counties as national designated poor counties. Provinces followed with their own initiatives. In our sample, Ningshan and Hanyin counties are nationally designated poor counties, and Shiquan is a provincially designated poor county.

in terms of characteristics like poverty rates, geography, fiscal capabilities and ethnic composition.

The students in the sample also appear to be similar, in line with what would be expected in a poor, rural setting in China. For example, we find 6% more boys than girls, a ratio similar to the 7% figure cited in the Ministry of Education's 2010 Annual Yearbook. Approximately 98% of the seventh graders in our sample are aged 11-15 years.

Although the main sample at the time of the baseline survey (September 2009) covered a total of 36 schools and 3121 students, there was some attrition by the time of the endline survey in September 2010 (figure 1)[3]. For various reasons (dropouts, absences, death, etc.), by the time of the endline survey we were only able to follow up with 2742 students—672 students in Ningshan County (the treatment group) and 2070 students in Shiquan and Hanyin counties (the control group). In spite of attrition of 379 students, the attrition rate is almost the same (12%) in both groups, thus reducing the probability of attrition bias.[4]

Table 1 shows that students in the study were similar in the key dependent variable (raw math test score in 2009—row 1). More specifically, the mean math score in the Ningshan County (treatment group) was 54.82, statistically similar to the mean math score of 53.29 in the Shiquan and Hanyin counties. There was no statistically significant difference between them. Moreover, rows 2 to 13 show that there were no statistically significant differences in most control variables: whether the student attended preschool, a sibling dummy for the student and an occupational dummy for the parent.

The fundamental difference between Ningshan and Shiquan/Hanyin Is that neither Shiquan nor Hanyin had a tuition relief program. We believe that this constitutes a quasi

[3] It is possible that information getting out about the program led to fewer students dropping out prior to grade 7 (i.e. prior to the baseline) in county schools in the tuition relief program. Two things suggest this is not a problem. First, we found that only 15% (the baseline) of the students and their parents knew about the program. Second, comparing school records from June 2009 (grade 6) and September 2009 (grade 7) show two things: one is that the dropout rate over this timeframe is less than 1%; the other is that dropout rates were almost identical between counties (1.03% in the county tuition relief program county schools, in Ningshan, and 1.09% in the control schools).

[4] The attrition rate, while high, is not unusual. In a working paper based on data from a county in Shanxi province (Di et al, 2011), the dropout rate of poor rural students between the first month of the first year of junior high (grade 7) and first month of the second year of junior high (grade 8) is reported to be 13.3 percent.

experiment, so we designate students in Ningshan as treatment students and students in Hanyin and Shiquan as control students. That is, as opposed to the 7th graders in Ningshan County who knew about the tuition relief program in senior high school, students in the control group who are in their first year of junior high school were fully aware of the fact that if they wanted to go to high school they (or their parents) would have to pay tuition.

Sampling and Data Collection

To evaluate the effectiveness of the tuition relief program, we collected data in Ningshan County and the two control counties, Shiquan and Hanyin. All 36 junior high schools in the three study counties were surveyed. In addition, in Ningshan County, all seventh grade classes in all six junior high schools were selected. In Shiquan and Hanyin counties, a subset of seventh grade classes in each of the 30 junior high schools was randomly selected[5] because Shiquan and Hanyin had a larger population (and it would have been too costly to survey all students in all classes).

We surveyed every student in each sample class, for a total of 3121 seventh graders surveyed. These students were in 69 classes across 36 junior high schools.

Two surveys were conducted: the baseline survey in early September 2009 at the beginning of the autumn semester and our evaluation survey, almost precisely one year later in September 2010. The enumeration team visited each school to conduct both rounds of the survey.

There are two blocks in each wave of our survey. The first block of the survey was a 30 minute standardized math test. This test was given to all sample students in both the treatment group and the control group. The survey/test was designed, printed and administered by ourselves. Since the test was administered at the beginning of the school year, we also know that neither students nor teachers shifted their efforts from other subjects to math. Moreover, even if the students knew about the program, rural students seldom take extra tutoring classes during summer vacation. As such, the math test scores we collected in early September can reasonably be used as the pre-

[5] As a first step, we selected all the junior high schools in the control county. Then, in each school, we randomly selected about one-third of the classes.

program outcome. When we gave the standardized tests, the connection to the treatment (the tuition relief program) was kept blind in both the treatment and control schools. In order to do so, none of the enumerators were informed about the goal of the survey except for a core staff of the two lead enumeration team managers.

For ease of interpretation, we report raw math test scores out of one hundred. We also use the normalized z-score of the math score to check the robustness of the results. The normalized score was created by subtracting the average test score of all sample students from the raw score for each student and then dividing it by the standard deviation of the test scores of all sample students in the same grade. The normalized test score following this transformation is interpreted as the number of standard deviations from the mean score across all students in the same grade. When we replicate our empirical analyses using normalized scores, the results are almost the same.

In the second block of the survey, enumerators collected data on the demographic and socioeconomic characteristics of students and their families. This part of the survey allows us to create our control variables. The dataset includes measures of each student's *age* (measured in years), *gender* (equal to one for boys, and zero for girls), *no sibling* (equal to one for students with no siblings and zero for students with siblings) and *preschool* and *kindergarten* (equal to one if students attended either preschool or kindergarten and zero otherwise), father and mother's *age* (in years), father and mother's *education level* (*completed at least middle school*) and father and mother's *occupation* (equal to one if a student's parent works in agriculture and zero if the parent works in the non-agricultural sector).

As part of the second block, students were also asked to indicate which assets their family owned from a list of 30 household assets. We use this data to generate an asset index using principal component analysis to measure the wealth of each household. Following the method used by Filmer and Pritchett (1998), we used scoring factors from the first principal component to create the asset index. This is essentially a weighted average of the 30 observed asset variables, and variables with higher coefficients have more weight in determining the score. The higher the asset indexes, the wealthier the household is. Based on this asset index, we divided the students into five quintiles, referred to as *poorest, second, median, fourth and richest*.

Analytical Approach

In this section we introduce our analytical approach. Our analysis uses DD, DDD, PSM and DDM as alternative approaches to estimating the impact of the tuition relief program.

Basic estimation methodology

We would like to determine the average treatment effect on the treated (ATT),[6] which is the average impact of the program on the treated (Smith and Todd, 2005). We thus use the following DD model to estimate the average treatment on the treated.

$$\Delta Score_i = \alpha + \delta Program_i + \gamma Score\_09_i + \beta X_i + \varepsilon_i \qquad (1)$$

where, i indexes the student, $\Delta Score_i$ is the change in the score of student i between 2009 and 2010; $Program_i$ is the treatment variable (i.e., δ is the parameter of primary interest). In our analysis, $Program_i = 1$ if student i participated in the program and is equal to zero otherwise.[7] Finally, the term X_i is a vector of covariates that are included to capture characteristics of the student, his/her parent and household, such as age, gender, whether the student attended preschool and number of siblings of the student, along with the educational attainment, occupation and age of the student's father and mother, and wealth status of the household.

Sensitivity Analysis

It is important to remember that one of the assumptions underlying the use of DD to identify the causal effect is the "parallel trend" assumption (Meyer, 1995). That is, in the absence of the policy change (or program intervention in our case), the average change in the outcome variable would have been the same for the treated and the comparison groups.

[6] In this case, the treatment is the introduction of the tuition relief program.

[7] "Participate in the program" means being a student in the county where such a program was introduced rather than being a recipient of the tuition relief.

As might be expected, the effectiveness of DD depends on the validity of this assumption. In this study, the difference in these differences can be interpreted as the causal effect of the tuition relief program under the assumption that, in the absence of program, the differences in the test scores of students would not have differed systematically between the treatment and control groups. This identification strategy would be invalid if the differences in student scores vary systematically across counties.

Since rich students might be not financially constrained when making decisions to go to senior high school, we do not necessarily expect them to be affected by the tuition relief program. We can thus use rich students as an additional control group to look at the effect of the tuition relief program on the test score of a poor student who might be affected by the tuition program. This allows us to define the difference-in-difference-in-differences (DDD) estimator. The model to be estimated is:

$$\Delta Score_i = \alpha + \delta \operatorname{Pr} ogram_i + \vartheta 1 \operatorname{Pr} ogram_i * Poor_i + \vartheta 2 Poor_i + \gamma Score\_09_i + \beta X_i + \varepsilon_i \qquad (2)$$

Where $Poor_i$ is the wealth indicator dummy for student i. This dummy is equal to one if the student's asset index is lower than the median and is zero if the asset index is higher than the median. Here, $\vartheta 1$ is the main coefficient of interest in this study.

We also use additional methods to obtain more robust findings. To begin with, we use the propensity score matching (PSM) method. With a sufficient region of support (or common support), it is possible to estimate the propensity scores of all students and compare the outcomes of students who either did or did not participate in the program but who have similar propensity scores.[8]

In our analysis, the observable covariates are characteristics related to the treatment and outcome variable, and are used to estimate the propensity score. We then use the nearest neighbour matching method (with replacement) to get the average treatment on the treated effect. The standard errors are adjusted for clustering at the school level and the standard errors are bootstrapped using 1000 replications.

Propensity score matching allows us to analyze the nature of the similarities between the treatment and control groups (both balance checks and graphs of common

8

support). There is substantial common support between the treatment and control groups. The treatment and control groups are similar after matching. The standardized percent bias (Rosenbaum and Rubin, 1985) for each of the covariates across our matched treated and control groups is small, especially for the covariates with relatively large differences (a large bias) in the means of the treatment and control groups in the pre-matched sample. The standardized percent bias (for each covariate) is defined as the % difference of the sample means in the treated and non-treated (full or matched) sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups (Leuven and Sianesi, 2003). For brevity, we only include one of the tables of the balance tests showing the results of the balancing test in the appendix. Full results are available from the authors upon request.

The PSM method is more general than standard linear regression in that it does not require assumptions about linearity or constant treatment effects, and thus improves bias correction. Moreover, imposing common support in PSM can lead to efficiency improvements, especially when the sample size is small.

Even though we control for observable individual differences when estimating the propensity score, there may still be systematic unobservable differences between the outcomes of students who did or did not participate in the program. The systematic differences could arise, for example, because the student's decision to participate is based on some unmeasured characteristics. Such differences could violate the identification conditions required for matching (Smith and Todd, 2005).

To eliminate the bias due to time-invariant unobservable differences between students who did or did not participate in the program, we will extend the cross-sectional PSM approach to a longitudinal setting and implement a difference-in-differences matching (DDM) strategy. With DDM we can exploit the 2009 data on the treated students to construct the required counterfactual data, rather than just using the 2009 data (cited effort is lower. However, this does not mean that the poorest students did not benefit. In fact, the poorest students saw their average scores rise by more than any group except the wealthiest (the difference in the rise between the treatment group and control group was 3.82—row 1). A puzzle arises in the nonlinearity of the results from the poorest to the richest. The second poorest students seem to benefit least from the program, with a difference in the rise between the treatment and control groups of only 1.17 points (column 7, row 2). Beyond this (as one moves from the second to the fifth group), scores generally rise (rows 3 to 5).

Why do the richest students respond most to the program? There are two likely explanations. First, we are only looking at descriptive statistics in table 3, which means that we are only comparing trends in single variables (i.e., they are not conditioned on other factors). Hence, the scores of the richer students may have risen due to factors which are specific to richer students and are also correlated with the treatment (in this case enjoyed by richer students in Ningshan), but are not directly related to the treatment itself. A second potential explanation is that the treatment is actually triggering a response among richer students that is leading to higher test scores. For example, the richest students, who did not previously have to compete with poorer students (who were effectively rationed out of senior high school by the high tuition rates), began to realize that they are losing one of their previous advantages in gaining entrance to senior high school. This may have led them to work harder. While we do not fully isolate the reason, in the next section we seek to control for the number of the observable characteristics of students using the regression models (1) through (4). If we control for as many factors as possible which differ between poor and rich students (e.g., the educational levels of their parents, etc.), we may be able to validate or invalidate potential explanations. Unfortunately, since the motivation behind this potential explanation is not observable, we cannot unambiguously confirm exactly what is driving our findings.

In sum, based on the descriptive statistics, the tuition relief program appears to increase the academic performance of students in the treatment schools. However, the effect of this program differs by wealth status: while the poorest students do gain from the program, surprisingly, it is the richest students who gain the most from the program.

Effect of the tuition relief program: Multivariate results

When analyzing the effect of the tuition relief program using a multivariate approach based on equation (1), the results are largely consistent with the descriptive statistics in terms of the overall impact (table 4). According to our analysis (and consistent with the findings in table 2), the tuition relief program has a positive and statistically significant impact on the students' test scores. The estimation of equation (1) demonstrates that the estimated treatment effect of the tuition relief program on math test scores is equal to 0.17 standard deviations and the impact is significant at the 10% significance level (row 1, column 1). That is, when we use a difference-in-differences approach, we find that the tuition relief program positively and significantly impacted students' average academic effort, as measured by the scores of the standardized tests.

Importantly, the results of our multivariate analysis differ from the descriptive statistics in terms of the effect of the tuition program on the poorest students in the sample (those with the lowest asset indices). As seen in table 4 (column 2), when we control for all of the covariates and then add an interaction term to connect the treatment variable (tuition relief program dummy) with a dummy variable representing the poorest students, we find that the program's effect is primarily on the poor. This result may have been "disguised" in the descriptive statistics. Specifically, while the average treatment effect (which in this case is the average treatment effect for all of the students except the poorest) is still positive, at 0.14, the standard error is relatively large. This high standard deviation means we cannot reject the hypothesis that the tuition relief program's effect on all but the students in the poorest asset category is zero. Specifically, the coefficient on the *poorest*program* interaction variable is large (0.23), positive and significant, indicating that the test scores of the poorest junior high students are 0.23 standard deviations higher than that of other students. If we take the multivariate results seriously, then the results as a whole (both descriptive and multivariate) demonstrate that the tuition relief program increased student academic performance in junior high school. More importantly, the poorest students, who were most likely to be from families which were financially constrained, benefited most from the program.

Effect of the tuition relief program: Matching results

As mentioned above, the difference-in-differences methodology relies on assumptions of parallel trends. That is, we assume that students in Ningshan (the treatment county) would have improved at the same rate as students in Hanyin and

Shiquan had there been no policy. However, one could argue that this result can be attributed to characteristics which are particular to Ningshan County. For example, Ningshan students (and in particular poor students in Ningshan) may be receiving more attention in junior high school and—even without the tuition relief policy—would have improved their test scores at a higher rate. In order to examine the robustness of our results using other approaches, we employ PSM and DDM analysis in this section to see if results from these different estimation strategies are consistent with those from the DD estimates above.

In fact, the results of both the PSM and DDM analyses are fairly similar to the DD results[9] (table 5). Rows 1 to 3 present the estimated average treatment effects on the treated (ATTs) of different treatment groups. Columns 1 and 2 show the estimation results, respectively from PSM and DDM. The PSM results show that the program positively impacted Ningshan students' average math scores relative to the control counties. The effect is 0.18 standard deviations and is significant at the 1% level (row 1). Likewise, when using difference-in-differences matching (DDM), the average treatment effect is 0.15 standard deviations and is significant. The average impact on test scores when using PSM (0.18) and DDM (0.15) is close to the average impact when using DD alone (0.17).

The results of the PSM and DDM also show that the greatest impact of tuition relief appears to be on the scores of the poorest students (table 5, rows 2 and 3). When we use PSM, the average test scores of the poorest students in the treatment group improved by 0.28 standard deviations more than the poorest students in the control group. Moreover, this result is statistically significant (row 2, column 1). By contrast, the point estimate of the impact of the tuition relief program on the richest students in the treatment group is 0.12 standard deviations higher than the improvement of the richest students in the control group, although this gain is not statistically significant (row 3,

[9] The treatment and control groups are similar after matching. The standardized percent bias (see Rosenbaum and Rubin, 1985) for each of the covariates across our matched treated and control groups is small, especially for the covariates that have a relatively large difference in treatment and control means (a large bias) in the pre-matched sample. The standardized percent bias (for each covariate) is defined as the percentage difference of the sample means in the treated and non-treated (full or matched) sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups (see Leuven and Sianesi, 2003). Full results are available from the authors upon request.

column 1). As for the DDM results, they show that the tuition relief program has a statistically significant impact on the test scores of junior high students. Moreover, this impact is significant for the poorest students, but the program does not appear to have any effect on the richest students (column 2, rows 2 and 3).

In sum, all three estimation strategies show that the program improves junior high students' math scores by more than 3 points. Moreover, the poorest students are indeed benefitting from the program. The only discrepancy is that the difference-in-differences results suggest that the richest students gained most from the program, whereas the PSM and DDM results suggest that the richest students may not have benefitted.

Effect of the tuition relief program by test scores

Our final empirical exercise tests a hypothesis that aims to account for both the institutional realities of China's competitive schooling system and observations on the behaviour of parents and students within this competitive system. Specifically, in this section we want to test the hypothesis that the one of the largest impacts of the tuition relief program may appear in the middle of the test score distribution.

This exercise is motivated by the fact that—even if senior high school were free—China's high schools require students to pass a competitive entrance exam. If a student's test score is too low (indicating that the student is among the poorest performing students in the county), the student would have little hope of getting a high enough score to enter high school even if the tuition relief program led him/her to work harder. This would be especially true of the poor, who cannot afford extra tutoring to effectively increase their grades. Then again, the families of top students in the county always seem to find a way to obtain sufficient resources to keep their child in school, even when they are poor. Indeed, a number of recent studies (e.g., Wang et al, 2011) found that high performing children—even very poor ones—find a way to continue with their schooling. This logic suggests that poorly performing students have given up and the best performing students have already decided to go to high school regardless of the cost. Hence, it seems that a tuition relief program might be expected to have an even larger effect on students from poor families whose test scores are in the middle of the test score distribution than on poor families as a whole.

The PSM results in table 5 show that the program has a positive effect on the math scores of the poorest students with a mid-range test score in Ningshan (compared to the poorest mid-range students in the control counties). The effect is 0.43 standard deviations and is significant at the 5% level (row 4). Likewise, when using difference-in-differences matching (DDM), the average treatment effect is 0.37 standard deviations and is significant. In sum, the results of both PSM and DDM show that the tuition relief program significantly improves the score of the poorest junior high students who score in the middle of the test score distribution.

Summary and Discussion

In this paper we have exploited a quasi experiment to examine the effect of a senior high tuition relief program on junior high students in poor, rural schools in Shaanxi province in China. Seeking to understand whether a tuition relief program improved the academic performance of junior high students, we compared seventh grade students in Ningshan County, where a tuition relief program was implemented, to seventh graders in the nearby Shiquan and Hanyin counties. We fielded a survey and administered a standardized math test, then analyzed the data using various estimation strategies such as difference-in-differences, difference-in-difference-in-differences, propensity score matching and difference-in-difference matching.

In most cases (except for the richest students), the descriptive and econometric results of the program effect were robust. In general, we found that the Ningshan tuition relief program positively impacted students' academic performance. Indeed, we find that the rise in math scores differs significantly between the control and treatment groups across all of the descriptive statistics and models used in this paper. That is, student might exert a greater level of effort years ahead of time when they expect to be able to afford to continue with their study. If parents know this when their children are younger, this could impact some children's effort from the very start.

More importantly, we also found that all of the multivariate approaches show the tuition relief program to have had the largest (and only significant) impact on poorest students. In short, and perhaps unsurprisingly, our findings demonstrate that the test scores of the poorest students rose by more (and significantly so) than that of other nonpoor students. Our data also shows that the positive impact of the tuition relief program was not statistically significant for the richest students, who are seldom financially constrained when making decisions about whether to continue to senior high school. This result supports the validity of the assumption in the DD analysis.

Taken together, these results may suggest that poor students work harder when they realize their families can afford high school tuition. However, it is important to realize that other potential mechanisms exist. For example, teachers—whose wages are linked to student matriculation in highly ranked high schools—may invest more time teaching poorer students who would have otherwise dropped out after ninth grade for financial reasons. Regardless of the mechanism, what we see here is that the tuition relief program clearly and positively impacts students' academic performance far before ninth grade. The final results of the paper also suggest that the impact is concentrated on students in the middle of the test score distribution. As such, if China wants to encourage students—even poorly performing students—to stay in school, other strategies also need to be used.

As cautioned above, our conclusions must be considered in cognisance of the limitations of this study. Even though we used multiple estimation strategies that consistently pointed to the positive impact of the Ningshan tuition relief program, we believe that it is important to extend the present study in order to confirm the robustness of the findings of this quasi experiment. Additionally, as a program implemented in just one county, we cannot make strong generalizations. Even if students in Ningshan benefitted from the program, this may result from county-specific characteristics.

Nonetheless, to our knowledge, this is the only study that explores the impact that the expectation of a tuition relief program in senior high school has on junior high student's efforts in China. Moreover, this study shows that a tuition relief program in senior high school has impacts as early as seventh grade. To truly improve poor rural students' likelihood of continuing on to senior high school, strategies that have impacts early in students' educational careers are particularly important. Reducing the academic performance gap early in students' career should give poor students a much better chance at continuing on to senior high.

Finally, the results of this study contribute to a broader policy debate about how to effectively invest in rural education. Recently, the Ministry of Education (MOE) has exhibited increased support for greater investment into rural education. Opinions are divided on how associated resources should be invested. Our results suggest that China's top educational officials should at least provisionally expand tuition relief programs in poor rural areas as an additional way to improve human capital in rural areas. If future evaluations of tuition relief programs confirm our results in other areas, China should consider waiving senior high tuition for all poor students.

References

Angrist, J., E. Bettinger, E. Bloom, E. King and M. Kremer. 2002. "Vouchers for Private Schooling in Colombia: Evidence from a Randomized Natural Experiment." *American Economic Review*, 92:5, pp. 1535-58.

Angrist, J. D. and V. Lavy. 2009. "The Effect of High-Stakes High School Achievement Awards: Evidence from a Group-Randomized Trial." *American Economic Review*, 99:4, pp. 1384-1414.

Ankang Statistics Bureau. 2009. "Statistical Communiqué on Economic and Social Development in the Prefecture of Ankang in Shaanxi Province in 2008," http://www.shaanxi.gov.cn/0/1/65/365/371/67147.htm.

Banerjee, A., S. Jacob, M. Kremer, J. Lanjouw and P. Lanjouw. 2000. "Promoting School Participation in Rural Rajasthan: Results from Some Prospective Trials." mimeo, MIT.

Banerjee, A. 2004. "Educational Policy and the Economics of the Family." *Journal of Development Economics*, 74:1, pp. 3-32.

Cai F. 2007. "Lewis Turning Point is Just Ahead." *Social Security in China*, 5, pp. 24-26 (in Chinese).

Carneiro P., M. Lokshin, C. Cano and N. Umapathi. 2011. "Average and Marginal Returns to Upper Secondary Schooling in Indonesia," IZA DP No. 6162.

Chuang, H. 1997. "High School Youths' Dropout and Re-enrollment Behavior." *Economics of Education Review* 16:2, pp. 171-186.

Deininger, K. 2003. "Does Cost of Schooling Affect Enrollment by the Poor? Universal Primary Education in Uganda." *Economics of Education Review* 22:3, pp. 291-305.

Deming, D. 2011. "Better Schools, Less Crime?" *The Quarterly Journal of Economics*, 12:4, pp. 2063-2115.

Glewwe, P. and M. Kremer. 2006. "Schools, Teachers, and Education Outcomes in Developing Countries." In E.A. Hanushek and F. Welch, eds. *Handbook of the Economics of Education*. Amsterdam: North Holland, 943-1017.

Huang, J., H. Zhi and Z. Huang. 2011. "The Impact of the Global Financial Crisis on Off-farm Employment and Earnings in Rural China." *World Development* 39:5, pp. 797-807.

Loyalka P., Y. Song, J. Wei and S. Rozelle. 2010. "Information, College Decision and Financial Aid: Evidence from a Cluster-randomized Control Trial in China." REAP Working Paper, Stanford University.

Leuven, E. and B Sianesi. 2003. "PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing." Statistical Software Components S432001, Boston College Department of Economics, revised 19 Jul 2012.

Li H. W. Liu, N. Ma and J. Zhang. 2006. "Does Education Pay in Urban China? Estimating Returns to Education Using Twins." Discussion Papers, Chinese University of Hong Kong.

Lincove, J. A. 2012. "The Influence of Price on School Enrollment Under Uganda's Policy of Free Primary Education." *Economics of Education Review* 31:5, pp. 799-811.

Liu C., L. Zhang, R. Luo, S. Rozelle, B. Sharbono and Y. Shi. 2009. "Development Challenges, Tuition Barriers and High School Education in China." *Asia Pacific Journal of Education*, 29:4, pp. 503-520.

MacLeod, W.B. and M. Urquiola. 2009. "Anti-Lemons: School Reputation and Educational Quality." National Bureau of Economic Research Working Paper 15112.

Meyer B. D. 1995. "Natural and Quasi-experiments in Economics." *Journal of Business and Economic Statistics,* 13:2, pp. 151-161.

Ministry of Education. 2009. "160 million students in Primary and Junior High Schools have benefitted from the Free Tuition Program." http://edu.people.com.cn/GB/10039775.html (in Chinese).

Ministry of Education. 2010. "National Educational Reform and Development Plan for Mid-Term and Long-Term (2010-2020)." http://www.gov.cn/jrzg/2010-07/29/content_1667143.htm (in Chinese)

Mo D., L. Zhang, H. Yi, R. Luo, S. Rozelle and C. Brinton. 2011. "School Dropouts and Conditional Cash Transfers: Evidence from a Randomized Controlled Trial in Rural China's Junior High Schools." REAP Working Paper 225, Stanford University.

Ohba, A. 2011. "The Abolition of Secondary School Fees in Kenya: Responses by the Poor." *International Journal of Educational Development*, 31, pp. 402-408.

Reardon, S. and C. Galindo. 2002. "Do High-Stakes Tests Affect Students?" Decisions to Drop Out of School? Evidence from NELS." Paper presented at the Annual Meeting of the American Educational Research Association. New Orleans, LA.

Rosenbaum, P. and D. B. Rubin. 1985. "Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score." *American Statistician*, 39, pp. 33-38.

Rozelle, S., L. Zhang, R. Luo, H. Yi and Y. Shi, 2012. "Avoiding the Middle Income Trap: Rural Education, Health and Building the Skills Needed in China's 21st Century Economy." Working Paper. REAP, Stanford University.

Sala-i-Martin X., G. Doppelhofer, and R.I. Miller, 2004. "Determinants of Long-term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach." *American Economic Review*, 94:4, pp. 813-835.

Sirin, S.R. 2005. "Socioeconomic Status and Academic Achievement: A Meta-analytic Review of Research." *Review of Educational Research, 75*:3, pp. 417-453.

Smith, J. and P. Todd. 2005. "Does Matching Overcome Lalonde's Critique of Nonexperimental Estimators?" *Journal of Econometrics*, 125, pp. 305-353.

UNESCO Institute for Statistics. 2011. Global Education Digest. Comparing Education Statistics Across the World: Focus on Secondary Education. http://www.uis.unesco.org/Education/Pages/ged-2011.aspx.

Valenzuela, A. 2000. "The Significance of the TAAS Test for Mexican Immigrant and Mexican American Adolescents: A Case Study." *Hispanic Journal of Behavioral Sciences*, 22, pp. 524-539.

Velez, W. and R. Saenz. 2001. "Toward a Comprehensive Model of the School Leaving Process Among Latinos." *School Psychology Quarterly*, 16, pp. 445-467.

Wang X., C. Liu, L. Zhang, R. Luo, T. Glauben, Y Shi., S. Rozelle and B. Sharbono. 2011. "What is Keeping the Poor out of College?: Enrollment Rates, Educational Barriers and College Matriculation in China." *China Agricultural Economic Review*, 3:2, pp. 131-149.

White, K. 1982. "The Relation Between Socioeconomic Status and Academic Achievement." *Psychological Bulletin,* 91, pp. 461-481.

Wooldridge J. M. 2010. Econometric Analysis of Cross Section and Panel Data. Boston: The MIT Press.

Yang D. 2006. *Equitable Education in China: Dream and Reality*. Peking University Publishing House (in Chinese).

Yi H., L. Zhang, R. Luo, Y. Shi. S. Rozelle and J. Chu, 2012. "Impact of the Tuition Relief Program in Senior High School on Junior High Students' Matriculation Rate to Senior High School: Evidence from a Natural Experimentl in Rural China." REAP working paper, Stanford University.

Zhang, J., Y. Zhao, A. Park and X. Song. 2005. "Economic Returns to Schooling in Urban China, 1988 to 2001." *Journal of Comparative Economics*, 33, pp. 730-752.

Appendix

Table 1. Sample average for students in the treatment and control groups in 2009 a

		(1) Treatment group	(2) Control group	(3) Difference in mean (1)-(2)
(1)	Raw math test score in 2009 (full score=100)	54.82	54.29	0.54
		(15.29)	(17.33)	(0.72)
(2)	Age of student (years)	12.92	13.06	-0.14
		(0.81)	(1.00)	(3.28)***
(3)	Male student (%)	49.18	53.20	-4.02
		(0.50)	(0.50)	(1.81)*
(4)	Student attended kindergarten (%)	16.47	15.15	1.31
		(0.37)	(0.36)	(0.82)
(5)	Student attended preschool (%)	93.26	93.19	0.07
		(0.25)	(0.25)	(0.06)
(6)	Student with no siblings (%)	28.27	25.89	2.38
		(0.45)	(0.44)	(1.21)
(7)	Age of father (years)	39.48	40.62	-1.14
		(4.78)	(5.08)	(5.02) ***
(8)	Age of mother (years)	36.73	37.64	-0.91
		(4.26)	(4.72)	(-4.34) ***
(9)	Father completed middle school (%)	44.13	38.33	5.79
		(0.50)	(0.49)	(2.65) ***
(10)	Mother completed middle school (%)	36.87	24.52	12.35
		(0.48)	(0.43)	(6.16) ***
(11)	Father mainly worked in agriculture (%)	33.04	30.10	2.94
		(0.47)	(0.46)	(1.43)
(12)	Mother mainly worked in agriculture (%)	51.34	49.86	1.48
		(0.50)	(0.50)	(0.67)
(13)	Number of family members	4.25	4.47	-0.23
		(1.07)	(1.15)	(4.42) ***

Data: Authors' survey
Notes: Standard deviations are reported in parentheses for columns (1) and (2);
Absolute values of t-statistics are reported in column (3);
Significant at 10% (*), 5% (**) and 1% (***) levels.

Table 2. Change in student math score between 2009 and 2010[a]

		Full sample	Treatment group	Control group	Difference (t-statistics in parenthesis)
	Panel A Change in raw math score				
		(1)	(2)	(3)	(4)=(2)-(3)
(1)	Mean score in 2009	54.42	54.82	54.29	0.53 (0.72)
		(16.85)	(15.29)	(17.33)	
(2)	Mean score in 2010	70.44	73.19	69.55	3.64 (4.96)***
		(16.61)	(15.49)	(16.87)	
(3)	Difference=(2)-(1) (t-statistics in parenthesis)	16.02 (35.45) ***	18.37 (21.88)***	15.26 (28.71)***	3.11 (2.96)***
	Panel B Change in normalized math score [b]				
(4)	Mean score in 2009		0.02	-0.01	0.03 (0.72)
(5)	Mean score in 2010		0.17	-0.05	0.22 (4.96)***
(6)	Difference=(2)-(1) (t-statistics in parenthesis)		0.15 (2.82) ***	-0.04 (1.45)	0.19 (2.99)***

Data: Authors' survey.

Notes:

a. Standard deviations are reported in parentheses in row (1) and (2); and absolute values of t-statistics are reported in parentheses in row (3) and column (4). Significant at 10% (*), 5% (**) and 1% (***) levels.

b. The normalized scores were created by subtracting the average test score in one year of all sample students from the test for each student and then dividing each score by the standard deviation of the test scores of all sample students in the same grade.

Table 3. Change in student math score between 2009 and 2010, by 2009 wealth[a] 2009, Shaanxi Province, China

		Treatment group			Control group			(7)	
		(1)	(2)	**(3)**	(4)	(5)	**(6)**		
		Score in 2009	Score in 2010	**Diff.=(2)-(1)**	Score in 2009	Score in 2010	**Diff.=(5)-(4)**	**Diff.=(3)-(6)**	
Change in raw score by wealth									
(1)	Poorest	54.86	75.00	**20.14**	51.99	68.31	**16.32**	**3.82**	(1.81) *
(2)	Second	55.34	73.53	**18.20**	52.86	69.88	**17.02**	**1.17**	(0.69)
(3)	Median	55.43	73.15	**17.72**	55.13	69.13	**14.00**	**3.72**	(2.35) **
(4)	Fourth	52.68	71.60	**18.92**	54.30	69.69	**15.39**	**3.52**	(2.22) **
(5)	Richest	56.22	73.93	**17.70**	57.57	70.89	**13.32**	**4.38**	(2.39) **
Change in normalized math score by wealth									
(6)	Poorest	0.03	0.28	0.25	-0.14	-0.12	0.02	**0.23**	(1.84) *
(7)	Second	0.05	0.18	0.13	-0.09	-0.03	0.06	**0.07**	(0.71)
(8)	Median	0.06	0.16	0.10	0.04	-0.08	-0.12	**0.22**	(2.37) **
(9)	Fourth	-0.10	0.07	0.17	-0.01	-0.05	-0.04	**0.21**	(2.22) **
(10)	Richest	0.11	0.21	0.10	0.19	0.03	-0.16	**0.26**	(2.39) **

Data: Authors' survey.

Notes:

a. Asset Index is created to measure the wealth using principle component analysis. To be specific, following the method by Filmer and Pritchett (1998), we use the scoring factors from the first principal component to create the asset index. It is in fact a weighted average of the observed 30 variables of assets and variables with higher coefficients have more weight in determining the score on this component. The higher the asset index is, the wealthier the household is. In Panel A and B, the sample students are divided into five groups based on the asset index, ranging from the poorest to the richest.

b. Absolute values of t-statistics are reported in parentheses in column (7). Significant at 10% (*), 5% (**) and 1% (***) levels.

Table 4 Difference-in-differences regressions evaluating the effects of tuition relief program on the normalized math score of average students and poorest students, Shaanxi Province, China [a]

	Dependent variable ($\Delta Score_i$) = $Score_{i,2010} - Score_{i,2009}$		
		(1)	(2)
(1)	Program dummy (1=participated in the program)	0.171	0.140
		(1.82)*	(1.50)
(2)	Poorest dummy [b] (1=Poorest)		-0.045
			(0.73)
(3)	Interaction term of Poorest and Program dummy (Program*Poorest)		0.230
			(2.99)***
(4)	Normalized math score in 2009	-0.034	-0.034
		(28.89)***	(28.85)***
(5)	Age of student (years)	-0.127	-0.128
		(6.01)***	(6.25)***
(6)	Gender dummy(1=boy,)	0.161	0.162
		(2.91)***	(2.95)***
(7)	Kindergarten dummy (1=attended the kindergarten,)	0.111	0.113
		(1.85)*	(1.87)*
(8)	Preschool dummy (1= attended preschool)	0.175	0.181
		(1.94)*	(2.02)*
(9)	One child dummy (1= one child)	-0.076	-0.078
		(1.29)	(1.35)
(10)	Age of father (years)	0.007	0.007
		(1.27)	(1.31)
(11)	Age of mother (years)	-0.004	-0.005
		(0.77)	(0.86)
(12)	Education dummy for father (1= father completed middle school)	0.045	0.046
		(1.20)	(1.23)
(13)	Education dummy for mother (1= mother completed middle school)	0.060	0.062
		(1.23)	(1.28)
(14)	Occupation dummy for father(1=work in agriculture)	-0.045	-0.047
		(0.88)	(0.89)
(15)	Occupation dummy for mother(1=work in agriculture)	0.025	0.026
		(0.59)	(0.61)
(16)	Number of family members (person)	0.004	0.003

		(0.17)	(0.14)
(17)	Second poorest dummy [c] (bottom 20%- bottom 40%)	0.034	
		(0.46)	
(18)	Median dummy [c] (bottom 40%- bottom 60%)	-0.012	
		(0.22)	
(19)	Second richest dummy [c] (Top 20%- Top 40%)	0.007	
		(0.10)	
(20)	Richest dummy [c] (>Top 20% quintile)	0.003	
		(0.04)	
(21)	Observations	2264	2264
(22)	R-squared	0.31	0.31

Data: Authors' survey.

Notes:

a. The dependent variable is the change in the normalized math test score and the standard errors are adjusted for clustering at the school level.

Absolute values of t-statistics are in parentheses. Significant at 10% (*), 5% (**) and 1% (***) levels.

b. The poorest dummy is the same as table 3. It equals 1 if the household asset index is in the bottom 1/5.

c. The wealth dummies are the same as in table 3 and the comparison group is the poorest (bottom 0-20%) students.

Table 5. Evaluating the effects of tuition relief program on the efforts of different type of students in using propensity score matching and difference-in-difference matching, Shaanxi Province, China [a,b].

		Propensity score matching [a,b]		Difference-in-difference matching	
		(1) Average treatment effect for the treated	*t*-stat/ z-value [b]	(2) Average treatment effect for the treated	*t* stat/ z-value [b]
(1)	Average students	0.18	(2.95) ***	0.15	(2.42) ***
(2)	Poorest students[c]	0.28	(1.80)*	0.28	(1.69)*
(3)	Richest students	0.12	(0.82)	0.08	(0.53)
(4)	Poorest students who scored at mid-range (20-80%) in 2009	0.43	(2.04)**	0.37	(1.88)*

Data: Authors' survey.

Notes:

[a] Propensity scores are estimated using the same set of covariates as in table 4. The balancing property is satisfied in all cases.
Specifically, we compare the characteristics of students in the treatment control groups (row 1); the poorest students, respectively in the treatment and control groups (row 2); the richest students, respectively in the treatment control groups (row 3); and poorest students with a mid-range score in 2009, respectively in the treatment and control groups (row 4).
t statistics are reported for propensity score matching. The standard errors were bootstrapped using 1000 replications; Significant at 10% (*), 5% (**) and 1% (***) levels.

[b] The matching method used is nearest neighbour matching method (random draw version) with replacement.

c. Poorest students are students whose asset value is the lowest (0-20%) among all students.

Figure 1: Experiment Profile

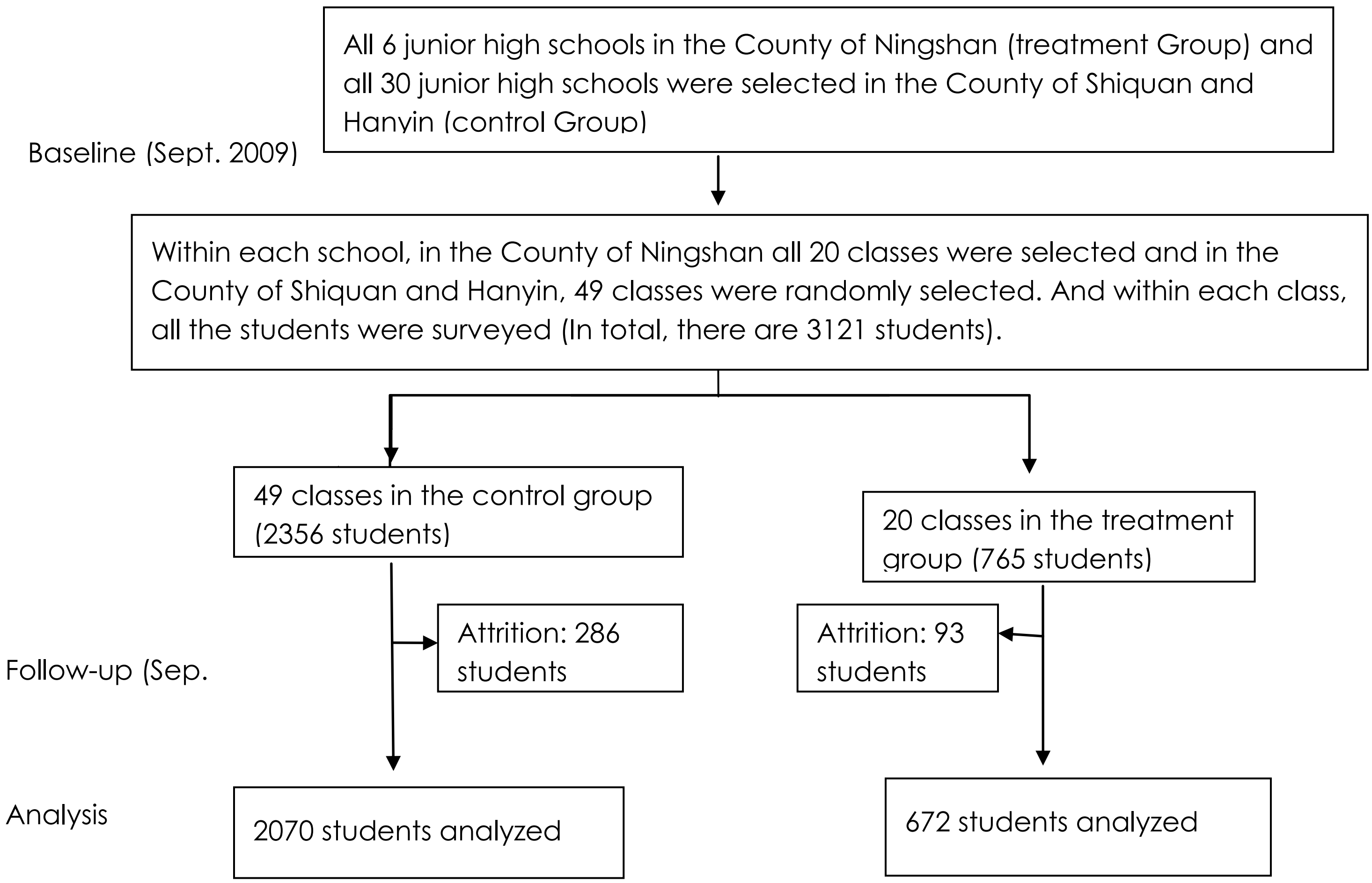

Table A1. Balancing test results when comparing the score between students in the treatment group and students in the control group

	Variable	Sample	Mean		%bias	t test	
			Treated	Control		t	p>|t|
(1)	Normalized math score in 2009	Unmatched	0.01	0.00	1.3	0.27	0.79
		Matched	0.01	-0.02	3.3	0.56	0.57
(2)	Age of student (years)	Unmatched	12.92	13.03	-11.8	-2.32	0.02
		Matched	12.92	12.90	2.1	0.35	0.72
(3)	Gender dummy(1=boy)	Unmatched	0.49	0.53	-7.9	-1.63	0.10
		Matched	0.49	0.50	-2.1	-0.35	0.72
(4)	Kindergarten dummy (1=attended kindergarten)	Unmatched	0.16	0.15	2.7	0.55	0.58
		Matched	0.16	0.15	3.2	0.55	0.58
(5)	Preschool dummy (1= attended preschool)	Unmatched	0.94	0.94	-0.4	-0.08	0.94
		Matched	0.94	0.94	0.5	0.08	0.94
(6)	One child dummy (1= one child)	Unmatched	0.26	0.24	5.6	1.16	0.25
		Matched	0.26	0.27	-1.3	-0.22	0.82
(7)	Age of father (years)	Unmatched	39.44	40.57	-23	-4.70	0.00
		Matched	39.44	39.59	-3	-0.53	0.60
(8)	Age of mother (years)	Unmatched	36.72	37.59	-19.6	-3.97	0.00
		Matched	36.72	36.74	-0.5	-0.08	0.94
(9)	Education dummy for father (1= father completed middle school)	Unmatched	0.44	0.39	11.1	2.30	0.02
		Matched	0.44	0.45	-2.2	-0.38	0.71
(10)	Education dummy for mother (1= mother completed middle school)	Unmatched	0.35	0.24	24.6	5.24	0.00
		Matched	0.35	0.35	1.3	0.21	0.84
(11)	Occupation dummy for father(1=work in agriculture)	Unmatched	0.34	0.31	5.7	1.18	0.24
		Matched	0.34	0.35	-2.7	-0.46	0.65
(12)	Occupation dummy for mother(1=work in agriculture)	Unmatched	0.54	0.53	2.8	0.59	0.56
		Matched	0.54	0.56	-3.4	-0.57	0.57

(13)	Number of family members (person)	Unmatched	4.29	4.50	-19.6	-4.00	0.00
		Matched	4.29	4.26	3.1	0.57	0.57
(14)	Second poorest dummy (bottom 20%- bottom 40%)	Unmatched	0.21	0.20	1.6	0.33	0.74
		Matched	0.21	0.20	1.4	0.24	0.81
(15)	Median dummy (bottom 40%- bottom 60%)	Unmatched	0.24	0.18	15.2	3.24	0.00
		Matched	0.24	0.26	-3.3	-0.52	0.60
(16)	Second richest dummy (Top 20%- Top 40%)	Unmatched	0.26	0.19	17	3.61	0.00
		Matched	0.26	0.26	0	0.00	1.00
(17)	Richest dummy (>Top 20% quintile)	Unmatched	0.18	0.20	-5.3	-1.08	0.28
		Matched	0.18	0.16	6.3	1.13	0.26