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TARGETED POVERTY ALLEVIATION AND CHILDREN'S ACADEMIC PERFORMANCE IN CHINA

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This paper estimates the causal impact of China's targeted poverty alleviation program on the academic achievement of students from poor households. We use the longitudinal academic records of a cohort of students from all middle schools in a nationally designated poor county in China. Using the difference-in-differences approach, we show that targeted poverty alleviation improves the scholastic performance of girls and their achievement rank among peer students. However, we find no such empirical evidence for boys. Our findings suggest that the new anti-poverty program in China has the potential to ameliorate the intergenerational transmission of low socioeconomic status to girls by promoting their human capital accumulation.

JEL Codes: I21, I32, I38

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1. INTRODUCTION

The alleviation and elimination of poverty has been a constant objective of the international community. Ending all forms of poverty globally is ranked the first

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among the 17 Sustainable Development Goals of the United Nations between 2015 and 2030 (Tollefson, 2015). The lack of human capital is usually considered as one of the causes and consequences of impoverishment and underdevelopment (Brown and Park, 2002). The development and well-being of children may be adversely affected by their experience of growing up in low-income families (Broaded and Liu, 1996; Frijters *et al*., 2012; Loken *et al*., 2012; Jerrim *et al*., 2020). When poor households have limited resources allocated for children's education and development, poverty may perpetuate across generations via vicious circles. The design of effective anti-poverty policies is a major concern for both policymakers and researchers. If an anti-poverty strategy can augment the human capital levels of poor children, then their lifetime earnings potential may be increased, and the intergenerational transmission of poverty may also be alleviated. In this sense, social policies formulated to improve the well-being of poor families should be evaluated to a large extent by their educational effects.

This paper examines the causal impact of the recently implemented targeted poverty alleviation program in China on the academic performance of students from economically disadvantaged families. As the world's most populous developing country, China had achieved a dramatic reduction in the number of poor people in the last few decades by implementing three rounds of anti-poverty programs between 1986 and 2012 (Park *et al*., 2002; Park and Wang, 2010; Qin and Chong, 2018).[1] These programs reduced China's rural poor population from 125 million in 1986 to around 20 million in 2012 (Li *et al*., 2016; Liu *et al*., 2018).[2] From 2013 to 2020, China had proposed and implemented the targeted poverty alleviation strategy, which was the fourth round of China's major fights against poverty. This strategy focused on the elimination of poverty at the household level. The program made it mandatory for every identified low-income household to receive anti-poverty assistance, and households were not permitted to quit the program until the government officially acknowledged that they had been lifted out of poverty. At all levels of the government, there were tremendous efforts to implement this policy, and the government took anti-poverty as a major political task. Different from the previous three rounds of poverty reduction, targeted poverty alleviation highlighted the importance of meeting each poor household's specific needs. To achieve this, the government established an accurate mechanism to identify poor households and built up electronic archives to record the progress in combating poverty for each identified low-income household. The policy was strictly enforced with an aim to lift all impoverished population out of poverty by the end of 2020 (Liu *et al*., 2018).

We use administrative academic records of a cohort of students in the same grade from all middle schools in a nationally designated poor county in Guangxi Province, one of the most impoverished areas in China. In this county, the targeted poverty reduction program officially began in late January 2016 and ended in December 2019. The main empirical question we ask is whether the program

[1]The three rounds of poverty alleviation during 1986–2012 are: (i) development-oriented poverty relief from 1986 to 1993, (ii) national 8–7 poverty alleviation plan from 1994 to 2000, and (iii) entire-village advancement poverty alleviation from 2001 to 2012. Appendix A summarizes the history of these three poverty alleviation programs in China.

[2]Over the same period, China's rural poverty line had also been increasing. It rose from 482 *yuan* (at 2010 price) per person per year in 1985 to 1528 *yuan* in 2000, before reaching 2625 *yuan* in 2012 (Liu *et al*., 2018). These thresholds are below the national rural poverty line (around 4000 *yuan*) used in the targeted poverty alleviation program.

has a causal impact on the academic performance of students from disadvantaged households that received anti-poverty assistance. Using the difference-in-differences (DID) approach, we show that the targeted poverty reduction program has a positive and significant impact on poor students' test scores. Our results are mainly driven by the improved learning outcomes of girls whose families were supported by the program. Specifically, the policy has improved their overall academic performance by 0.04 standard deviations. In contrast, we find no such evidence for male students. Our dynamic analysis further illustrates that the beneficial academic impact for girls is observed in the results for certain exams within the first year of program implementation, but the impact is consistently significant for all exams in the second year.

We further explore the potential heterogeneity in the policy impact. The effects for girls are statistically significant on their achievement in Chinese and Math, but not in English, History, and Politics. In contrast, the exposure to targeted poverty assistance has no significant effect on the performance of male students in any subject. We also find evidence of heterogeneous effects depending on the head of the household. When a mother is the head of a poor household receiving policy assistance, the academic outcomes of her children have improved to a greater extent when compared with the father being the head of the household. There is no evidence that the policy impact differs by the number of children in low-income households. In addition, we show that the program improves the relative academic rank of girls in their school cohort. Overall, the targeted poverty alleviation program has the potential to break the intergenerational inheritance of low socioeconomic status to girls by promoting their human capital accumulation.

We contribute to the literature in the following ways. First, this paper provides the first evidence on the causal effect on student performance of the targeted poverty alleviation program in China, which is a novel strategy to eradicate absolute poverty at the household level.[3] Second, we use the administrative academic records of a cohort of students in the same grade from all middle schools in a nationally designated poor county. As these students were all receiving compulsory education, we are able to analyze the impact of targeted poverty reduction on their test scores without conditioning on school attendance.[4] The longitudinal nature of our data also allows us to investigate the dynamic academic effects of the initiative to fight against poverty. Last, the program enabled every identified poor household to receive anti-poverty assistance, and these households could not quit the program before being officially recognized by the local government that they had been lifted out of poverty. Unlike many other poverty-reduction policies, there is no self-selection of eligible poor households in participating in this program. As such, this study offers a rare case in the literature that the intent-to-treat effect of an anti-poverty strategy is the same as its average treatment effect on the treated.

[3]Other anti-poverty strategies evaluated in the extant literature include conditional cash transfers (Behrman *et al*., 2011; Dubois *et al*., 2012; Glewwe and Kassouf, 2012), unconditional cash transfers (Baird *et al*., 2011; Benhassine *et al*., 2015), and educational fee reforms (Schultz, 2004; Chyi and Zhou, 2014; Xiao *et al*., 2017).

[4]China has strictly enforced the Compulsory Education Law since 1986, which has significantly increased primary and middle school enrollment rates. Since 2010, the middle school enrollment rate of children aged 13–15 has been close to 100 percent in China (Yue *et al*., 2018). As for the county on which we focus in this paper, around 99.76 percent of children aged 13–15 attended middle schools in 2018, according to the education statistics of the local government.

The rest of the paper is organized as follows. Section 2 describes the institutional background. Section 3 introduces the data and presents the summary statistics. Section 4 discusses the empirical approach. Section 5 presents the estimation results. Finally, Section 6 concludes.

2. Institutional Background

2.1. *Targeted Poverty Alleviation in China*

China had proposed and implemented the targeted poverty alleviation strategy during 2013–2020, which was the fourth-round of China's major policy initiative to reduce poverty. In 2019 alone, the Chinese government allocated 91 billion *yuan* (approximately US$14 billion) to poverty-alleviation funds. Government departments were required to create electronic archives and to issue cards for each impoverished household recording their family status, income, and the support liaison person. A system was established to assess the performance of cadres responsible for providing policy assistance. From 2013 to 2020, around 98.99 million rural residents had been lifted out of poverty. All 832 impoverished counties and 128,000 villages had also been removed from the poverty list. In December 2020, the Chinese government announced that it had achieved the goal of eradicating absolute poverty. Building on this significant achievement, China is now moving on to push for higher-level rural development and vitalization.

2.2. *Targeted Poverty Alleviation in a Poor County in Guangxi Province*

We focus on a cohort of middle school students in one nationally designated county in China's Guangxi Province.[5] The county has an administrative area of 2500 square kilometers. In 2015, it had a population of around 367,800 from 180 villages in 12 townships, with many poor people living in villages with harsh natural conditions, weak infrastructure, and poor public services.[6]

According to the policies formulated by the State Council Anti-poverty Office and the Provincial Government of Guangxi, from October to December 2015, the county organized around 20,000 public servants and cadres to visit all households to collect detailed information about their economic status. To accurately identify eligible poor households, a rating system was established based on the characteristics of each household, including family income, dwelling conditions, basic food and clothing needs, ownership of durable goods, health conditions, health insurance status, children's education, and family size, among others. The scores of the rating system

[5]Guangxi is officially called the Guangxi Zhuang Autonomous Region, which is located in south China and borders Vietnam. It has a population of around 48.85 million, of which over 14 million are Zhuang people, the largest ethnic minority group in China. In 2018, Guangxi ranked the 28th in terms of GDP per capita and the 26th in terms of disposable income per capita, among the 31 provinces/autonomous regions/municipalities in mainland China.

[6]As per our agreement with the local government, we do not disclose the county by name. It was a typical poverty-stricken county in Guangxi Province. In 2015, its population size (367,800) was very close to the average size (368,400) of the 28 nationally designated poor counties in Guangxi Province. The average annual household income per capita in rural areas of the county was 6159 *yuan* in 2015, very similar to the corresponding average value of 6334 *yuan* in the 28 poor counties. The average income of rural households in the county ranked the 14th among the 28 poor counties in 2015.

ranged from 0 to 100, with a higher value indicating higher socioeconomic status. The county government used a score of 65 as the cutoff point. Namely, households with a score below 65 were classified by the local government as being qualified for the anti-poverty support. In our student data, the average rating score was 53.66 for those in low-income households and 74.15 in others. Therefore, the anti-poverty strategy was well targeted at the impoverished population in the county.

A total of approximately 70,000 individuals from 19,000 households living in 80 villages were identified as poor people in the county. The overall rate of poverty incidence was around 20 percent. Receiving targeted assistance was not on a voluntary basis. It was compulsory for every identified poor household to participate and they were not permitted to quit the program before they were officially recognized by the government to have been lifted out of poverty. As such, there was no self-selection of eligible poor households participating in this program.

The program of targeted poverty reduction officially began in late January 2016 and ended in December 2019 in the county. As most poor people live in rural areas, it was predominantly a rural program (although eligible poor households in urban areas also received policy support). The program included the following types of support: (i) a series of large farming subsidies (e.g., subsidies for planting hawthorns, mangoes, tobacco leaves, and poultry farming); (ii) business subsidies to boost employment/entrepreneurial activities of people designated as the poor (e.g., micro-credit loans and employment subsidy); (iii) housing improvements (renovation of dilapidated housing and relocation assistance); and (iv) education and health benefits (e.g., ensuring school attendance of all children of compulsory school age, nutritious-meal subsidy, enrollment subsidy, and medical-fee assistance). Some components of the implemented program (e.g., development support and education support) mattered particularly for the scholastic performance of poor students. Detailed descriptions of the targeted poverty reduction program implemented in the county appear in Appendix B. Criteria and procedures for households to be officially recognized as having shaken off poverty are shown in Appendices C and D, respectively.

This policy turned out to be an effective means to eradicate poverty in the county. According to the official statistics of the county, the average annual income of the identified poor households (at 2016 price) increased from 7264 *yuan* in 2016 to 9129 *yuan* in 2017, before further rising to 9325 *yuan* in 2018. Moreover, 4375 people from 1069 households in five villages and 15,753 people from 3821 households in 14 villages had been lifted out of poverty in 2016 and 2017, respectively. A further 28,102 individuals from 7063 households in 23 villages had shaken off poverty in 2018. Based on the local criteria (see Appendix C), a total of 48,230 people from 11,953 households in 42 villages (around 69 percent of poor population initially identified in the county) no longer lived in poverty by the end of 2018. In December 2019, the local government announced that all identified low-income households in the county had been successfully lifted out of poverty.

3. Data and Variables

This paper evaluates the causal impact of the targeted poverty alleviation program on the academic outcomes of students from economically disadvantaged backgrounds. We have access to the administrative records of a cohort of students in the same grade from all middle schools in the poor county. The data provided by the local Education Board include the information on students' academic outcomes and their individual characteristics. The anti-poverty office of the local government also offered the information on whether a student's family was exposed to targeted poverty alleviation or not. Our data tracked students who started middle school education in the fall semester of 2015 and followed them for two-and-a-half years (a total of five semesters) until the end of the fall semester of 2017. These students were from 77 classes in all the 15 middle schools in the county. These students in our data were all receiving compulsory education.

In China's education system, there are two semesters per year and two exams (a mid-term exam and a final exam) in a semester. We have information on the exam results for all subjects in those five semesters. The first two exams took place prior to the official launch of targeted poverty alleviation in the county and the remaining eight after it. Here we focus on five compulsory subjects (Chinese, Math, English, Politics, and History) that were taught in all three years of middle school. The exams were standardized within the county in terms of the same set of exam questions and an anonymous marking process. It is important to note that the full marks for Chinese, Math, and English were 120, while there were only 60 marks for Politics and History. We assign these relative weights when calculating the total marks in each exam for students in our data.

Table 1 presents the summary statistics of students when they took the first exam in middle school. We consider a student to be in the treatment group if his/her family became a beneficiary of targeted poverty reduction in late January 2016. Our final sample consists of 34,038 observations for 3673 students (643 in the treatment group and 3030 in the control group). Approximately 17.5 percent of students were from beneficiary households. Students were aged around 13 when starting education in middle school. Compared with the control group, poor students were more likely to be girls and have siblings. We find no significant difference in parental migration status between these two groups. Furthermore, about 77 percent of the students in the treatment group came from families headed by the father, and the share was 66 percent among those in the control group.

Table 1 shows some significant differences in individual characteristics between poor students and their richer counterparts. It is likely that these two groups also differ in unobservable ways. Consequently, a simple comparison of the exam results of students in the treatment and control groups does not reveal the causal impact of the targeted poverty alleviation program. The next section introduces the DID approach as our strategy for causal identification.

4. Identification Strategy

We use the following standard DID framework:

$$Y_{ict} = Treatment_i * Post_t * \beta + ClassbyExam_{ct} + \mu_i + \epsilon_{ict}, \tag{1}$$

where Y_{ict} denotes the measure of academic performance of student i in class c in the tth exam (t=1,2,...,10). $Treatment_i$ is a binary variable that equals to one if

TABLE 1
Students' Characteristics When Taking the First Exam in Middle School

	Control Group		Treatment Group		Differences (C–T)	
	Mean	S.D.	Mean	S.D.	Diff.	*p*-value
Age in September 2015	13.10	0.80	13.20	0.76	−0.10	0.00
Boy	0.51	0.50	0.38	0.49	0.13	0.00
Only child in the family	0.55	0.50	0.22	0.42	0.32	0.00
Parental migration status:						
Both parents have migrated for work	0.59	0.49	0.57	0.49	0.01	0.49
One parent has migrated for work	0.18	0.39	0.19	0.39	−0.01	0.68
No parent has migrated for work	0.23	0.42	0.24	0.43	−0.01	0.67
Household head is:						
Father	0.66	0.47	0.77	0.42	−0.11	0.00
Mother	0.23	0.42	0.10	0.30	0.13	0.00
Neither father nor mother	0.10	0.31	0.12	0.33	−0.02	0.16
The student is from a rural household	0.90	0.30	0.99	0.09	−0.09	0.00
Individuals	3030		643			

student i is in the treatment group, and $Post_t$ is a dummy variable equal to 1 if the tth exam took place after late January in 2016, when targeted poverty alleviation started. We also include class-by-exam fixed effects ($ClassbyExam_{ct}$) in our estimations to control for any observed or unobserved factors specific to each class in each exam. Moreover, μ_i denotes the individual fixed effects, which control for the individual-level time-invariant characteristics. ϵ_{ict} is the error term. In Equation (1), we have not separately included $Treatment_i$ and $Post_t$ as they can be perfectly predicted by individual fixed effects and class-by-exam fixed effects, respectively. We cluster the standard errors at the student level to account for heteroskedasticity and any arbitrary correlations across the academic outcomes of the same student.

The estimation of Equation (1) yields the average impact of targeted poverty reduction on students' academic achievement. It is likely that the academic influence of the program varies with the length of time that students were exposed to this policy. To analyze the possible dynamic influence, we also estimate the following DID model:

$$Y_{ict} = \sum_{t=2}^{10} Treatment_i * Exam_t * \beta_t + ClassbyExam_{ct} + \mu_i + \epsilon_{ict}. \quad (2)$$

This specification allows us to evaluate the policy impact on student performance in each exam after targeted poverty reduction started (t=3,...,10).

The validity of our DID approach is built on the assumption that the treatment and control groups would display comparable trends in academic outcomes, in the absence of the policy. Table 2 displays the standardized total test score and scores of each subject in the first two exams that took place before the implementation of

TABLE 2
Standardized Scores in the First Two Exams

	Control Group		Treatment Group		Differences (C–T)	
	Mean	S.D.	Mean	S.D.	Diff.	*p*-value
Panel A: Exam 1						
Total score	−0.00	1.02	0.01	0.91	−0.02	0.54
Chinese	−0.01	1.01	0.04	0.94	−0.05	0.46
Math	0.01	1.01	−0.05	0.93	0.06	0.34
English	−0.00	1.02	0.01	0.93	−0.02	0.51
History	0.00	1.01	−0.01	0.97	0.02	0.79
Politics	−0.03	1.00	0.14	0.99	−0.17	0.00
Panel B: Exam 2						
Total score	−0.00	1.02	0.00	0.91	−0.00	0.77
Chinese	−0.01	1.02	0.03	0.91	−0.03	0.95
Math	0.02	1.01	−0.07	0.93	0.09	0.13
English	−0.00	1.01	0.02	0.94	−0.03	0.25
History	−0.00	1.01	0.01	0.93	−0.01	0.69
Politics	−0.02	1.01	0.10	0.92	−0.12	0.04
Panel C: Exam 2–Exam 1						
Difference in total score	0.00	0.38	−0.01	0.39	0.01	0.36
Difference in Chinese	0.00	0.62	−0.01	0.59	0.01	0.35
Difference in Math	0.01	0.59	−0.02	0.62	0.03	0.62
Difference in English	−0.00	0.48	0.01	0.47	−0.01	0.36
Difference in History	−0.00	0.60	0.02	0.61	−0.03	0.23
Difference in Politics	0.01	0.71	−0.04	0.73	0.05	0.05

Note: Table A1 in Appendix E reports raw scores for the two groups in the first two exams.

targeted poverty alleviation. We report the scores for the treatment group and the control group separately. The Mann–Whitney test results in Panels A and B show that there is no significant difference in the overall academic performance between the two groups in the two exams. Table 2 also indicates no significant difference in subject achievement except in Politics.

To test the common-trend assumption, we follow the approach of Boes *et al.* (2015) to calculate the first differences in the test scores between the first two exams for both the treatment and control groups. They reflect trends of student performance before the anti-poverty program and are presented in Panel C of Table 2. The Mann–Whitney tests show no evidence of significant between-group differences in the pre-policy trends of overall academic performance and the test scores of four subjects. However, compared with the students in the treatment group, those in the control group show comparatively more improvement in their test scores for Politics from the first to the second exam. Nonetheless, this difference between the two groups is small in magnitude and the score of Politics only accounts for 12.5 percent ($=\frac{60}{480}$) of the total score of the five subjects in each exam (see Section 3). Therefore, Panel C of Table 2 shows that our data on overall academic performance support the parallel-trend assumption.

TABLE 3
Main Results for the Overall Sample

	(i)	(ii)
$Treatment_i{*}Post_t$	0.074***	0.029**
	(0.022)	(0.013)
Individual fixed effects	No	Yes
Class-by-exam fixed effects	Yes	Yes
Observations	34,038	34,038
Within R^2	0.002	0.273

Notes: The dependent variable is the standardized total score of five core subjects. Standard errors clustered at the student level appear in parentheses. $^{**}p < 0.05$; $^{***}p < 0.01$.

5. Results

5.1. *Main Results*

Table 3 reports the estimation results, using the pooled sample of male and female students. The dependent variable is the standardized total score of five core subjects (Chinese, Math, English, History, and Politics). We use two different model specifications. In specification (i), we only control for class-by-exam fixed effects. We find that targeted poverty alleviation is associated with an increase in the overall academic performance of poor students by 0.074 standard deviations. In specification (ii), we include both individual fixed effects and class-by-exam fixed effects (the DID specification in Equation (1)). The estimated coefficient displayed in column (ii) is much smaller than that reported in column (i). Our baseline DID estimation result shows that targeted poverty reduction leads to an increase of 0.029 standard deviations in the overall measure of academic performance of poor students. It should be noted that while the poverty alleviation program was targeted at low-income households, we are unable to completely rule out the possibility that this program may have an indirect positive effect on students in the control group. If such spillover influence exists, the estimate presented in column (ii) of Table 3 represents the lower bound of the true impact, which strengthens our conclusion.

We next examine whether the influence of the anti-poverty initiative varies with student gender. Table 4 reports the DID estimation results separately by gender. Here, we consider girls (boys) in higher-income families as the control group, and use the changes in their academic performance as the counterfactual for what would have happened to poor girls (boys), had targeted poverty alleviation not been implemented. We find that the targeted poverty alleviation improves the test scores of female students only. There is no statistical evidence that the policy has a significant impact on the learning outcomes of boys. We perform a test of the null hypothesis that the policy has equal effects for male and female students. We find the gender difference to be statistically significant with a p-value of 0.071. As such, only poor girls can benefit from the targeted poverty reduction program.

The increased economic resources available may have contributed to the positive linkage between targeted poverty reduction and the scholastic achievement of female students. When the program was launched in late January 2016, around 17.5 percent of students in our data were from low-income households identified by the local government. In January 2018 (when exam 10 took place), the proportion was reduced to 5.4 percent. Consequently, more than two-thirds of the poor

TABLE 4
Results by Gender

	Male	Female
$Treatment_i$* $Post_t$	−0.009	0.041***
	(0.023)	(0.016)
Individual fixed effects	Yes	Yes
Class-by-exam fixed effects	Yes	Yes
Observations	15,931	18,107
Within R^2	0.309	0.337

Notes: The dependent variable is the standardized total score of five core subjects. Standard errors clustered at the student level appear in parentheses. ***$p < 0.01$.

student households had been lifted out of poverty over those 2 years. During the same period, the proportion of poor male student declined from 14.5 percent to 3.9 percent, whereas the share for female students declined from 21.9 percent to 6.7 percent. Frijters *et al*. (2012) find that the increase in family income has had a positive and significant impact on student test scores in rural China. When compared with boys, girls' academic outcomes are more noticeably affected by family income. They attribute this gender difference to the son preference norm in the Chinese culture (Wang, 2005; Murphy *et al*., 2011): the education of girls is of less focus in rural households than that of boys. Hannum (2003) and Chyi and Zhou (2014) have made a similar argument that girls' schooling is particularly vulnerable to household financial constraints in rural China.

5.2. *Dynamic Effects*

Tables 3 and 4 report the average effects of the anti-poverty program on student performance in all post-policy exams. The estimated impact is likely to vary with the length of time that students' families were exposed to the policy. We estimate Equation (2) to uncover the possible dynamic effects. Figure 1 illustrates the estimated effects on the overall academic performance in each exam. Compared with the test scores in the first exam in middle school, the anti-poverty strategy has no discernable effect in the second exam which took place before the policy started. This confirms the results in Panel C of Table 2 that the common-trend assumption is satisfied in our data, even after we control for class-by-exam fixed effects and individual fixed effects.

Figure 1 shows that the policy does not have any impact for boys in exams following the launch of the program. In contrast, the policy exerts a positive and significant impact on girls' performance in the 4th and the 5th exams (p-values=0.062 and 0.017, respectively). Although the coefficient in the 6th exam is not significant at conventional levels, it remains positive. In all subsequent exams (7th–10th), the academic effects are positive and statistically significant for female students. We have conducted a F-test to check the null hypothesis that the poverty-alleviation policy has equal effects on female students' achievement in exams 7–10. We cannot reject the null hypothesis (p-value=0.457). Moreover, we find that the policy affects boys and girls differently in exam 4 (p-value=0.079) and exams 7–10 (p-values=0.012, 0.013, 0.029, and 0.087, respectively).

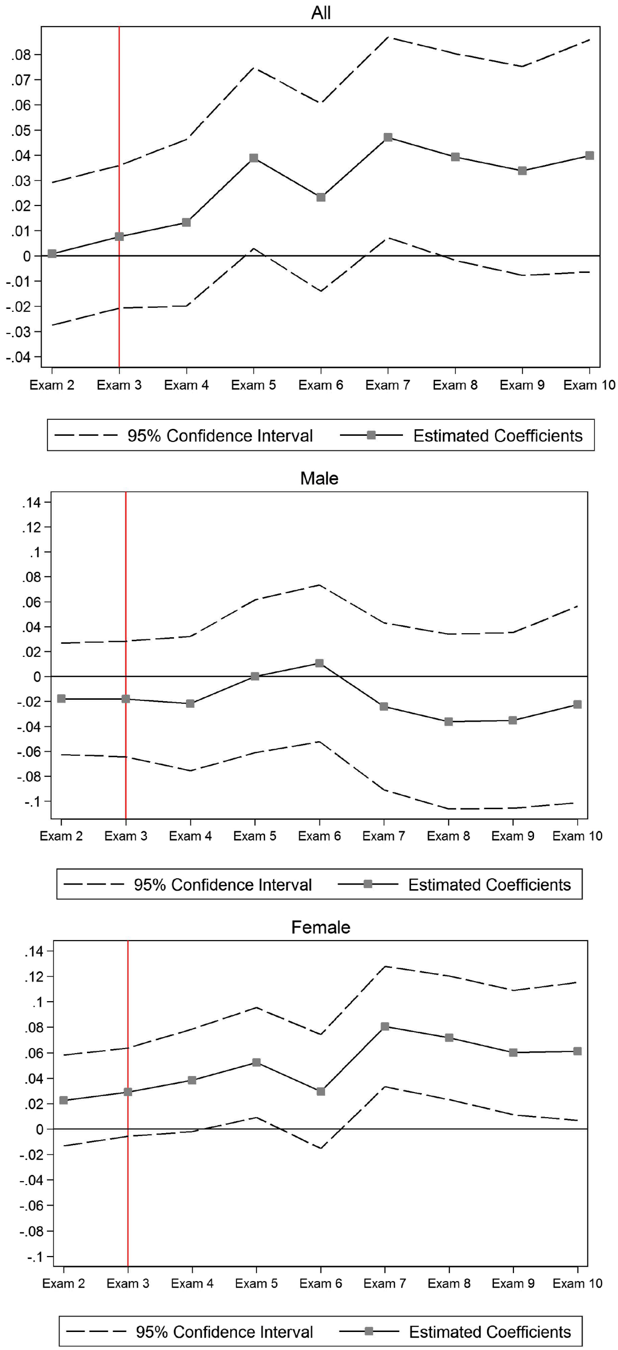

Figure 1. Dynamic Academic Effects of Targeted Poverty Alleviation [Colour figure can be viewed at wileyonlinelibrary.com]

5.3. *Heterogeneity Analysis*

In this section, we explore the potential heterogeneity in the effects of the targeted poverty reduction program on student performance. We focus on the possible differential effects across the following three dimensions: (i) subject, (ii) the household head, and (iii) whether a student is the only child in his/her household.

We first examine the program effects on the academic achievement in each subject (Chinese, Math, English, History, and Politics). With the alleviation of poverty in their households, poor students may direct the additional educational resources available to subjects such as Chinese and Math, which account for the largest proportion of the total score. In our estimations, the dependent variable for each subject is the test score standardized to have zero mean and unit-standard deviation. We perform the DID regressions using the same set of control variables as those in Table 4. Results appear in Table 5.

The DID estimates show that targeted poverty assistance has no significant effect on the exam performance of male students in any subject. However, for girls, targeted poverty alleviation improves their scholastic outcomes in Chinese and Math by 0.041 and 0.063 standard deviations, respectively. While the DID estimates are positive when standardized test scores of English, History, and Politics are used as the dependent variable, none of them are statistically significant. Therefore, the positive policy effect on the overall academic achievement of girls, shown in Table 4, is mainly driven by their enhanced academic outcomes in Chinese and Math, two of the three subjects that have the highest weights in the total score (as discussed in Section 3).

Next, we analyze whether the effects of targeted poverty reduction on student achievement differ by household headship status. The anti-poverty assistance has generated more resources available to poor households. The gender of the person who is the household head may matter for the amount of resources devoted to child development. Liu (2008) shows that rural children in China whose mother is the household head are generally taller than those whose father plays a decisive role in household affairs. Income in the hands of women is likely to generate greater effects on child well-being than income in the hands of men. Table 6 reports the differential effects by household headship status. Our results show that when a mother is the household head, the exam performance of a girl has improved to a larger extent by the anti-poverty policy than when her father is the household head (the reference group). In mother-headed households, the DID estimate is of a similar magnitude for boys, although it is not statistically significant.

As shown in Table 1, 55 percent of the students in the control group were the only child in their households, whereas only 22 percent in the treatment group had no siblings. We last examine whether the policy influence differs by the number of children in poor households. Results presented in Table 7 show no evidence that the academic impact of targeted poverty alleviation for a girl who is the only child in her family is different from that for a girl with siblings. Middle school education is part of China's 9-year compulsory education, which is tuition free. Because of the patriarchal culture of son preference, rural parents from impoverished households do not have much incentive and resources to invest in a girl's education, no matter whether she has siblings or not. Being the only child in a poor household does not necessarily indicate more resources available to a girl. In the targeted poverty alleviation program, a key component was that the local government provided a fixed amount of

TABLE 5
Effects on Subject Achievement

	Chinese	Math	English	History	Politics
Panel A: All					
$Treatment_i$* $Post_t$	0.045***	0.045**	−0.009	0.023	0.017
	(0.017)	(0.018)	(0.019)	(0.018)	(0.019)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Class-by-exam fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	34,038	34,038	34,038	34,038	34,038
Within R^2	0.210	0.218	0.153	0.237	0.257
Panel B: Male					
$Treatment_i$* $Post_t$	0.025	−0.027	−0.040	0.002	0.030
	(0.032)	(0.031)	(0.031)	(0.028)	(0.033)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Class-by-exam fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	15,931	15,931	15,931	15,931	15,931
Within R^2	0.248	0.257	0.163	0.278	0.273
Panel C: Female					
$Treatment_i$* $Post_t$	0.041**	0.063***	0.019	0.013	0.005
	(0.019)	(0.022)	(0.022)	(0.022)	(0.021)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Class-by-exam fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	18,107	18,107	18,107	18,107	18,107
Within R^2	0.279	0.275	0.244	0.294	0.337

Notes: The dependent variables are standardized score of each subject. Standard errors clustered at the student level appear in parentheses. ** $p < 0.05$; *** $p < 0.01$.

education-specific subsidy to each student (see Appendix B (vi)). As the educational subsidy available to each student did not vary with the number of children in a household, targeted poverty reduction has similar effects for girls with and without siblings.

5.4. *Impact on Achievement Rank*

Here we analyze the impact of targeted poverty alleviation on a student's ordinal rank in the test score distribution. Recent studies show that a student's ability rank in his/her cohort can exert long-run influences on educational attainment (Elsner and Isphording, 2017; Bertoni and Nistico, 2018), confidence and subject choices in secondary school (Murphy and Weinhardt, 2018), and scholastic performance and major choices in college (Elsner *et al.*, 2021).

To make the rank comparable across cohorts of different sizes, we follow Elsner and Isphording (2017) to convert the absolute ordinal rank (1, 2, 3, ..., N) into a percentile rank. We assign a value of 0 to the lowest-ranked student and a value of 100 to the highest-ranked student in a cohort with other ranks in between. Specifically, to calculate the relative rank within a class, we use the following formula:

$$\text{percentile rank} = \frac{\text{absolute ordinal rank in class} - 1}{\text{number of students in class} - 1} * 100. \tag{3}$$

TABLE 6
Effects by Household Headship

All	Male	Female	
$Treatment_i$* $Post_t$	0.014	−0.021	0.022
	(0.015)	(0.025)	(0.018)
$Post_t$ * Mother is household head	−0.061***	−0.054**	−0.066***
	(0.015)	(0.023)	(0.020)
$Post_t$ *Neither father nor mother is household head	−0.003	0.001	0.003
	(0.018)	(0.030)	(0.022)
$Treatment_i$* $Post_t$* Mother is household head	0.068	0.087	0.095**
	(0.042)	(0.071)	(0.048)
$Treatment_i$* $Post_t$* Neither father nor mother is household head	0.038	−0.006	0.044
	(0.043)	(0.075)	(0.043)
Individual fixed effects	Yes	Yes	Yes
Class-by-exam fixed effects	Yes	Yes	Yes
Observations	34,038	15,931	18,107
Within R^2	0.274	0.311	0.338

Notes: The dependent variable is the standardized total score of five core subjects. Standard errors clustered at the student level appear in parentheses. The pairwise interaction terms of $Treatment_i$ and household headship status can be predicted by individual fixed effects. **$p < 0.05$; ***$p < 0.01$.

TABLE 7
Effects by Only-Child Status

	All	Male	Female
$Post_t$* Only child	−0.040***	0.000	−0.030*
	(0.012)	(0.021)	(0.016)
$Treatment_i$* $Post_t$	0.019	−0.016	0.034**
	(0.015)	(0.030)	(0.017)
$Treatment_i$* $Post_t$* Only child	−0.001	0.021	0.020
	(0.034)	(0.050)	(0.044)
Individual fixed effects	Yes	Yes	Yes
Class-by-exam fixed effects	Yes	Yes	Yes
Observations	34,038	15,931	18,107
Within R^2	0.275	0.310	0.338

Notes: The dependent variable is the standardized total score of five core subjects. Standard errors clustered at the student level appear in parentheses. The pairwise interaction term of $Treatment_i$ and only-child status can be predicted by individual fixed effects. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

The within-school percentile rank and within-county percentile rank are calculated analogously. We then perform the DID regressions of the achievement rank variables on $Treatment_i{*}Post_t$, controlling for individual fixed effects and class-by-exam fixed effects. Results appear in Table 8.

Consistent with the results on test scores presented in Table 4, we find that targeted poverty alleviation improves the relative rank of girls in the distribution of test scores in the classroom. As the average class size is around 50 in our sample, a female student would have her ordinal rank of scholastic performance advanced by about one position in her class, if her household was a beneficiary of targeted

TABLE 8
Percentile Rank as the Outcome Variable

	Within-Class Percentile Rank			Within-School Percentile Rank			Within-County Percentile Rank		
	All	Male	Female	All	Male	Female	All	Male	Female
Treatment$_i$* *Post*$_t$	1.953***	−0.510	2.489***	1.254***	−0.600	1.680***	0.980**	−0.295	1.321***
	(0.678)	(1.111)	(0.821)	(0.467)	(0.782)	(0.544)	(0.395)	(0.673)	(0.452)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class-by-exam fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,038	15,931	18,107	34,038	15,931	18,107	34,038	15,931	18,107
Within R^2	0.309	0.297	0.397	0.213	0.243	0.292	0.271	0.307	0.339

Notes: The dependent variable is the within-cohort percentile achievement rank. Standard errors clustered at the student level appear in parentheses. $^{**}p < 0.05$; $^{***}p < 0.01$.

poverty alleviation. Similarly, at both the school and county levels, we find an improved achievement rank of female students from disadvantaged backgrounds. The estimates are negative but not statistically significant for poor boys. The gender differences in the DID estimates displayed in Table 8 are statistically significant with p-values being 0.030, 0.017, and 0.046, respectively.

5.5. *Robustness Checks*

5.5.1. PSM–DID Estimates

In this section, we perform a robustness check using the combined propensity score matching (PSM) and DID approach (PSM–DID). PSM has been widely used to summarize the observed characteristics into a single index termed the propensity score. Individuals in the treatment and control groups can be matched based on the propensity scores. We apply the probit model to estimate the propensity score to be in the treatment group for each student, using the observed characteristics displayed in Table 1 as covariates. Using $\widehat{p(x)}$ to denote the estimated propensity score, we follow Hirano *et al*. (2003) to generate weights that are equal to $\frac{1}{\widehat{p(x)}}$ and $\frac{1}{1-\widehat{p(x)}}$ for the treatment group and the control group, respectively. Focusing on the observations for students in the two groups with common support, we then perform the DID estimations using these weights. The PSM–DID approach allows us to focus on students in the two groups with comparable observed characteristics and to deal with unobserved confounders that are constant across time between the two groups.

Table 9 reports the PSM–DID estimation results. These estimates are close to those presented in Tables 3 and 4. As such, our main findings regarding the influence of targeted poverty reduction on student performance are robust when our estimation sample comprises students in the treatment and control groups with comparable observed characteristics.

5.5.2. Falsification Test

We have shown that the anti-poverty program has significantly improved the academic outcomes of female students only. One may speculate whether our findings are driven by unobserved factors. In this section, we randomly select 643 students from our sample and consider their households as the targets of the anti-poverty program. Then we conduct the DID estimations of Equation (1) with the falsified treatment variable. We repeat this process 1000 times and obtain the coefficient distributions for the overall sample, boys, and girls, respectively.

Figure 2 shows that the three coefficient distributions all center around zero, each with the lower bound of estimates being negative and the upper bound being positive. For girls, our baseline estimate (0.041 in Table 4) is larger than the 95th percentile (0.025) of the 1000 falsified estimates. Therefore, the positive and significant effect of the program on the academic achievement of girls is unlikely to be driven by unobserved factors. In contrast, our true estimate for boys (−0.009 in Table 4) lies between the 5th percentile (−0.025) and the 95th percentile (0.025) of the 1000 falsified estimates, confirming the insignificant impact of the anti-poverty program for boys.

TABLE 9
PSM–DID Estimates

	All	Male	Female
Treatment$_i$* *Post*$_t$	0.019	−0.010	0.035**
	(0.015)	(0.022)	(0.016)
Individual fixed effects	Yes	Yes	Yes
Class-by-exam fixed effects	Yes	Yes	Yes
Observations	34,038	15,931	18,107
Within R^2	0.312	0.389	0.382

Notes: The dependent variable is the standardized total score of five core subjects. Standard errors clustered at the student level are reported in parentheses. **$p < 0.05$.

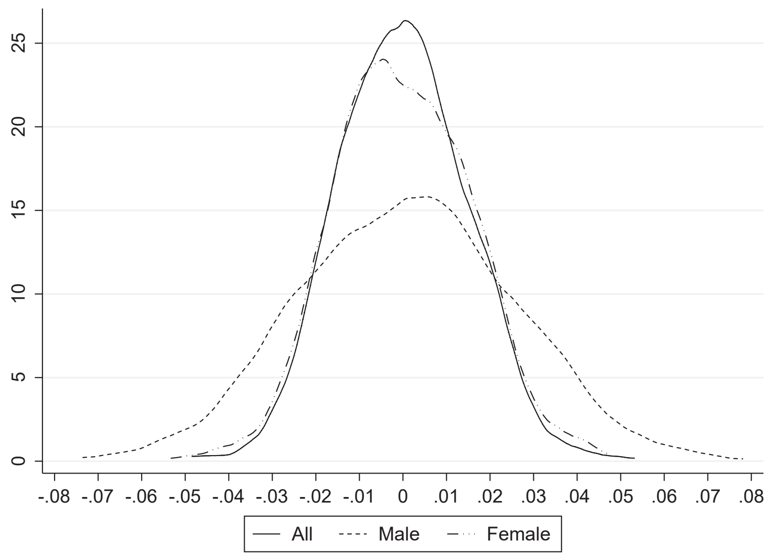

Figure 2. Distributions of Coefficients Estimates Using Falsified Treatment

6. Conclusion

In this paper, we analyze empirically the impact of China's targeted poverty alleviation program on the academic performance of poor students. To this end, we use longitudinal academic records of a cohort of students in the same grade in all middle schools from a nationally designated poor county in China's less developed Guangxi Province.

Using the DID approach, we show that targeted poverty reduction has a positive and significant impact on the scholastic achievement of poor students. Our gender analysis suggests that this beneficial influence is driven by the improved academic performance of girls whose families were supported by the anti-poverty program. The positive impact for female students emerges within the first year of policy implementation, but only for some of the exams. In the second year, the impact on the exam performance of girls is consistently positive and significant for all exams. In addition, we show that the program improves the relative academic rank of girls in their school cohort. In contrast, there is no evidence of any impact of the policy on the academic performance of male students or their achievement rank among peers. We attribute this gender difference to the deep-rooted patriarchal norms and the culture of son preference in China. Rural parents adhering to the son preference norm generally give priority to investment on their sons' education, rather than on their daughters'. A relaxation of financial constraints in poor households likely benefits girls more than boys. Consequently, the anti-poverty program has a more noticeable impact on the test scores of girls.

Overall, our analysis identifies the positive effects of targeted poverty alleviation on the scholastic performance of girls from low socioeconomic backgrounds. This program has helped promote the human capital accumulation of girls from poor households, which may increase their lifetime earnings potential and ameliorate the intergenerational transmission of economic disadvantage to them. Although it is difficult to assess the size of the potential multiplier effects from improved academic outcomes of girls, our results point out the potential of substantial returns to the strategy to combat poverty.

A few caveats apply to our findings. First, as targeted poverty alleviation in the county was started in late January 2016, we are only able to identify its short-term effects on student performance. Second, the anti-poverty strategy had different components in effect at the same time, so it is empirically challenging to isolate the impacts of specific policy components. These two aspects are important areas for future research.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher’s web site:

Appendix A: Overview of China’s first three rounds of poverty alleviation
Appendix B: Targeted poverty alleviation implemented in the poor county during 2016–2019
Appendix C: Criteria for low-income households to be officially recognized as having shaken off poverty in the poor county
Appendix D: Procedures for low-income households to be officially recognized as having shaken off poverty in the poor county
Appendix E: Raw scores in the two exams before targeted poverty alleviation
Table A1: Raw scores in the first two exams