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The peer effect on the academic performance of rural left-behind children

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ABSTRACT

In the context of China's dual economic structure, rural left-behind children often face prolonged parental absence, increasing their reliance on peer influence. This paper explores peer effects on math achievement using an instrumental variable approach, based on a sample of 2604 rural primary students in Shaanxi province. The results show that peers' math performance significantly improves left-behind children's scores by 0.678 standard deviations, with the strongest influence from their first- and second-best friends. Heterogeneity analysis reveals that peer effects are stronger among left-behind girls, non-boarding students, and those with moderate baseline academic performance. Mechanism analysis suggests that peer influence work through enhanced perceptions of mathematics, increased learning confidence, and improved study habits. These findings highlight the need to address educational challenges faced by left-behind children to enhance rural human capital development.

1. Introduction

In many developing countries, rapid economic growth has driven rural populations to urban areas in search of better employment opportunities. This migration has resulted in a widespread phenomenon of "left-behind children"—those who remain in rural areas while their parents migrate to cities or abroad (Ratha et al., 2011; Vanore et al., 2021). These children often face emotional stress, educational disruption, and reduced parental supervision.

China's rapid economic development has intensified this trend, particularly due to the dual urban-rural household registration (hukou) system and financial barriers that prevent migrant children from enrolling in urban schools (Yang & Duan, 2008; Yuan & Zheng, 2016). As a result, a large population of children are left behind in rural communities. In 2020, over 12.9 million rural children in compulsory education—41.8 % of all rural students—were left behind (China Statistical Yearbook, 2021). Their academic and emotional development is significantly affected by parental absence, with documented consequences for nutrition, learning, and mental health (Chang et al., 2019; Cortes, 2015; Liu et al., 2021; Meng & Yamauchi, 2017; Zhang et al., 2014; Zhao et al., 2014). Approximately 96 % of these children are cared for by grandparents (Ministry of Civil Affairs of the People's Republic of China, 2018), who can manage basic caregiving tasks but often struggle to provide adequate educational support due to lower levels of education (Duan & Zhou, 2005; Hu et al., 2020).

Extensive research has examined peer effects, particularly those linked to academic performance and cognitive ability. Many

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studies find that high-achieving peers positively impact individual academic performance (Carman & Zhang,2012; Feld & Zölitz, 2017; Yuan et al., 2018). For example, a randomized trial in Beijing showed that seating high- and low-achieving students together improved low-achievers' performance by 0.256 standard deviations. However, other studies report null or even negative peer effects (Angrist & Lang, 2004; Lavy et al., 2012; Xu et al., 2020). In addition to academic ability, peer characteristics such as gender, mobility, and physical attributes have also been found to influence educational and behavioral outcomes (Chen et al., 2021; Gong et al., 2021; Hu, 2015, 2018; Li, 2014).

This paper investigates the peer effects on mathematics performance among left-behind children using data from 2604 third- to sixth-grade students in 60 rural elementary schools in western China. Employing instrumental variables and fixed effects methods, we find that peer academic performance has a significant positive impact on academic performance, particularly among left-behind children. Further, we find that peer influence operates primarily through changes in students' motivation, learning behavior, and academic engagement.

Our contributions to the literature are as following. This study focuses on peer effects among rural left-behind children in primary schools—a group that receives limited academic and emotional support due to prolonged parental absence caused by labor migration (Fan et al., 2010; Zhang et al., 2014; Khatia et al., 2020; Nguyen, 2016; Botezat & Pfeiffer, 2020). At this emotionally sensitive developmental stage, peers may play a critical role in compensating for missing parental involvement. While previous literature has extensively examined peer effects and left-behind children separately, few studies have investigated the intersection of these two areas, particularly at the primary level and with academic outcomes (Ammermueller & Pischke, 2009; Burke & Sass, 2013; Cortes, 2015; Fellmeth et al., 2018; Gu, 2023; Hu, 2018; Huang & Zhu, 2020). To our knowledge, only one existing study addresses peer effects among left-behind children, and it focuses on mental health in junior high students (Wang & Zhu, 2021).

This paper fills that gap by examining how peer relationships affect academic achievement—a crucial indicator for student development and long-term human capital formation. To improve the identification of peer influence, we adopt a peer nominate approach that allows students to identify their closest peers by name, offering a more behaviorally grounded measure of peer groups than traditional classroom-based proxies. In addition, we explore potential mechanisms—such as learning anxiety, study behavior, and peer academic interaction—through which peers shape educational outcomes. These contributions provide a deeper understanding of peer dynamics among a vulnerable and underexplored student population.

The rest of the paper is organized as follows. Section 2 describes the data sources and variable construction. Section 3 details the empirical strategy and model specifications. Section 4 presents the findings of the empirical analysis. The final section concludes the study and discusses its implications.

2. Data and variable

2.1. Data

The data used in this study was collected by the Center for Experimental Economics in Education at Shaanxi Normal University. The primary goal of the survey was to understand the relationship between rural teachers' participation in subject-specific training and students' academic performance. The survey was conducted in September 2014 using a three-step sampling strategy.

First, two rural prefectures in Shaanxi province were selected. The average per capita income of rural residents in Shaanxi Province was RMB 8687 (approximately USD 1278), which is lower than the national rural average of RMB 8896 (approximately USD $1316), making Shaanxi representative of low-income rural areas in China NBS, 2014).

Second, based on the number of counties in each prefecture, we randomly selected 9 counties from City A and 10 counties from City B, resulting in a total of 19 counties.

Third, we compiled a list of all rural primary schools in these counties, excluding those located in county towns and those not offering grades 1–6. From the eligible schools, we randomly selected 20 schools from City A and 40 schools from City B, resulting in a final sample of 60 schools. Students in grades 3–6 in these schools constitute our sample population.[1]

The project team conducted a follow-up study of the sample schools in January 2015. During both survey periods, students completed standardized math tests and questionnaires that gathered information on personal characteristics, family background, and academic status. Data collection was carried out by specially trained researchers following a standardized protocol. In addition, math teachers of the sample classes completed separate questionnaires. After excluding urban samples, cases lost to follow-up, and samples with missing data, the final analytical sample consists of 2604 valid questionnaires. Table 1 displays the sample size by different categories.

2.2. Variable setting

2.2.1. Dependent variable

Academic performance is measured by students' mathematics test scores, as math provides an objective and readily available measure compared to other subjects. To ensure grade-level appropriateness, test items were designed by experienced elementary math

[1] Grades 1 and 2 were excluded from the study because the survey required students to complete a self-administered questionnaire. Prior experience showed that younger students often lack the literacy and comprehension skills needed to respond reliably. To ensure data quality, we limited our sample to students in grades 3–6.

Table 1
Sample sizes by location, school, and grade level.

	Number of counties	Number of schools	Total number of students	Third grade	Fourth grade	Fifth grade	Sixth grade
Total Sample	19	60	2604	1127	357	604	516
City A	9	20	1208	716	29	165	298
City B	10	40	1396	411	328	439	218

Data source: Author's survey.

teachers in accordance with national curriculum standards. All students in grades 3–6 completed the same 35-min standardized math test. Scores were standardized by grade, with a mean of 0 and standard deviation of 1, to enable consistent cross-grade comparison (See Table 2).

2.3. Independent variables

The primary explanatory variable is the average math scores of a student's peers. Students were asked to name up to five best friends within their classes. The mean of the standardized math scores of these nominated peers serves as the main measure of peer academic performance (See Table 2).

2.4. Control variables

Following prior studies (Quan & Lu, 2020), the model includes three sets of control variables: individual characteristics, peer characteristics, and teacher/classroom characteristics. Individual and family characteristics include gender (0=male, 1=female), age (in years), grade level (3rd grade=0, 4th grade= 1, 5th grade=2, 6th grade=3)[2] , boarding status (0=non-boarder, 1=boarder), and lagged standardized math scores (mean=0, standard deviation=1). Family characteristics include household economic status (measured by reported household assets)[3] and parental educational attainment (a continuous variable ranging from 0 to 12 years).[4] Peer characteristics are measured by the number of self-nominated peers. Teacher and class characteristics encompass teacher education level (0 = less than college, 1 = college and above), years of teaching experience (in years), teacher gender (0 = male, 1 = female), teacher title (0 = level 2 and below, 1 = level 2 above), and class size (total number of students) (See Table 2).

3. Methods

3.1. Baseline model

Drawing upon the theoretical framework of the educational production function, we estimate the following baseline OLS model to identify the peer effects on the academic performance of left-behind students.

$$Y_{ij} = \beta_0 + \beta_1 P_{ij} + \beta_2 X_{ij} + \beta_3 T_{ij} + \tau_j + u_{ij} \tag{1}$$

In this model, Y_{ij} is the standardized math score of student i in school j. P_{ij} is the mean peer standardized mathematics score of student i's self-nominated peers. The vector X_{ij} is a set of individual- and family-level control variables, including lagged standardized math scores, gender, age, boarding status, family economic status, and years of parental education. The vector T_{ij} includes teacher-, class-, and school-related characteristics. τ_j represents school fixed effects. u_{ij} is the random disturbance term. The primary parameter of interest is the coefficient β_1, which quantifies the effect of peers' mean math achievement on students' academic performance.

3.2. Models for endogeneity

This study addresses three primarily endogeneity concerns in estimating peer effects. Firstly, the average peer achievement variable P_{ij} in the baseline OLS model (Eq. (1)) potentially endogenous due to "self-selection bias". That is the tendency of students to choose peers with similar backgrounds, such as those with similar grades or of the same gender. To mitigate this issue, we adopt two strategies. First, this study focuses exclusively on rural left-behind children, excluding urban samples. In rural China, students typically attend schools based on their "hukou" (household registration) rather than through school choice or entrance exams, which helps reduce selection bias in peer formation. Second, we include a comprehensive set of student and family controls, such as lagged standardized

[2] Four dummy variables were generated for the four grade levels, with 3rd grade serving as the control group.

[3] Since it is difficult to obtain accurate information about students' household income through questionnaires, this study employed an alternative approach. We collected data on students' household assets as a proxy variable for household income and conducted a principal component analysis to obtain indicators that reflect students' household asset status.

[4] The values from 0 to 19 represent the following categories, no schooling, no elementary school graduation, elementary school graduation, no junior high school graduation, junior high school graduation, no high school or secondary school graduation, high school or secondary school graduation, no college graduation, college graduation, no university graduation, university graduation, above university graduation, respectively.

Table 2
Descriptive statistical analysis of variables.

	N	Mean	Std. dev.	Min	Median	Max
Student Academic Performance						
Standardized math scores	2604	0.001	0.998	-3.213	0.106	2.838
Standardized math scores (lag period)	2604	0.000	0.996	-3.531	0.024	3.506
Peer academic performance and characteristics						
Average standardized math scores	2604	0.126	0.627	-2.776	0.153	1.887
Average standardized math scores (lag period)	2604	0.104	0.609	-1.978	0.111	1.939
Number of peers	2604	4.392	1.050	1	5	5
Education of peer fathers (in years)	2604	9.515	1.955	0	9.375	16
Education of peer mothers (in years)	2604	9.451	2.290	0	9.3	16
Personal and Family Characteristics of Students						
Left-behind children (1=yes, 0=no)	2604	0.504	0.500	0	1	1
Age (in years)	2604	9.997	1.393	6.417	9.833	13.917
Female (1=female, 0=male)	2604	0.482	0.500	0	0	1
Boarding (1=yes, 0=no)	2604	0.086	0.280	0	0	1
Father's education (in years)	2604	9.365	3.371	0	9	16
Mother's education (in years)	2604	9.297	3.713	0	9	16
Family Assets	2604	-0.009	1.149	-2.258	-0.059	1.967
Teacher Characteristics						
Math teacher's teaching experience (in years)	2604	15.511	7.052	0.100	14	39
Math teacher's gender (1=female, 0=male)	2604	0.853	0.355	0	1	1
Math teacher's education (1=college and above, 0=below college)	2604	0.258	0.437	0	0	1
Math teacher's title (1=level 2 above, 0=level 2 and below)	2604	0.198	0.398	0	0	1
Class size (number of students)	2604	44.589	17.326	9	45	90

Data source: Author's survey.

math scores, gender, age, family assets, and parents' educational attainment.

Secondly, we address "correlation effects", which arise because students and their peers share the same school environment, including teachers and classroom conditions. If not controlled for, such shared influences may lead to an overestimation of peer effects. We control for classroom- and teacher-level characteristics and include school-fixed effects to account for unobserved institutional factors and reduce this source of bias.

Lastly, we consider the "reflection problem", which refers to simultaneity in peer effects: peers influence an individual's academic performance, while the individual may simultaneously influence their peers. To address the potential endogeneity of peer selection, we use the average years of education of the parents of a student's self-nominated close friends (within the same classroom) as an instrumental variable (Min et al., 2019). Each student was asked to nominate up to five close friends from their own class. This socially constrained peer nomination process minimizes the scope for strategic selection, as the peer pool is limited and relatively homogeneous in both academic context and social exposure. Furthermore, in rural China, parental education levels are generally low and exhibit limited variation across families. This feature reduces the likelihood that students systematically select peers based on their parents' education levels. As such, we aim to exploit variation in family background that is plausibly exogenous within the classroom setting. While we recognize that the exclusion restriction may not be perfectly satisfied, we believe this IV offers a reasonable approximation for identifying peer effects in a setting where randomized peer assignment is infeasible. We also control for school and grade fixed effects in all regressions to further account for institutional-level confounders. The two-stage least squares (2SLS) models are as follows.

First stage regression model:

$$P_{ij} = \alpha_0 + \alpha_1 Fa\_edu + \alpha_2 Mo\_edu + \alpha_3 X_{ij} + \alpha_4 T_{ij} + \tau_j + \varepsilon_{ij} \tag{2}$$

Second stage regression model:

$$Y_{ij} = \beta_0 + \beta_1 \widehat{P}_{ij} + \beta_2 X_{ij} + \beta_3 T_{ij} + \tau_j + u_{ij} \tag{3}$$

In Eq. (2), P_{ij} represents the peer standardized math score, *Fa_edu* and *Mo_edu* represent the average years of education of peers' fathers and mothers, respectively. The first-stage regression generates the fitted values of $\widehat{P}_{ij}$, which are then used in the second-stage (Eq. (3)) to yield unbiased estimates of β_1, the peer effect.

To compare peer effects between left-behind and non-left-behind students, we also estimate the model using 2SLS estimation separately for each group. To test whether the peer effects differ significantly across the two subgroups, we use the Bootstrap method

(Efron & Tibshirani, 1994) to evaluate the null hypothesis H0: d0 = 0, where d0 denotes the difference in coefficient estimates. The empirical p-value from the bootstrap procedure indicates the likelihood of observing the actual differences under the null hypothesis.[5]

4. Empirical results

4.1. Descriptive statistics

Table 2 reports descriptive statistics for the main variables. Among the sample students, 50.4 % were left-behind children, defined as those with one or both parents living away from home. Table 3 compares key characteristics between left-behind and non-left-behind children.

Regarding academic achievement, left-behind children scored significantly lower on standardized math tests than their non-left-behind peers. However, no significant difference was observed in the lagged period. In terms of peer characteristics, left-behind children were surrounded by peers with significantly lower average math scores, both current and lagged, as well as lower average parental education levels.

Family background also differed notably: parents of left-behind children had relatively fewer years of education, and their families faced more economic hardship. In contrast, there were no significant differences between the two groups in terms of age and gender. However, left-behind children were more likely to be boarders at school.

4.2. OLS estimation results of peer effects

Table 4 reports the results from OLS regressions estimating the impact of peer achievement on individual student performance. In the full sample (Column 1), a one standard deviation increase in peer math scores is associated with a 0.164 standard deviation increase in a student's math score, significant at the 1 % level. This relationship is similarly strong for left-behind children (Column 2, coefficient=0.162) and non-left-behind children (Column 3, coefficient=0.164).

Overall, the OLS results suggest a significant positive peer effect on student achievement across both groups. However, a bootstrap test comparing the two coefficients yields an empirical p-value of 0.478, indicating no statistically significant difference in peer effects between the left-behind and non-left-behind children in the OLS framework.[6]

4.3. 2SLS estimation results of peer effect

Table 5 reports the 2SLS regression results along with diagnostic tests for instrument validity. In the first stage, the instrumental variables—the average years of education of peers' fathers and mothers—are significantly and positively associated with peers' average math scores. These instruments pass key validity tests: the under-identification test ($p = 0.00$), the weak instrumental test (F-value > 10), and the over-identification test (insignificant p-values), confirming their relevance and validity.

The second-stage results show that, in the full sample, a one standard deviation increase in peer achievement leads to a 0.359 standard deviation increase in individual achievement, significant at the 10 % level. Among Left-behind children, the effect is even stronger: a 0.678 standard deviation increase for every one standard deviation increase in mean peer scores. In contrast, the effect for non-left-behind children is smaller (0.135) and statistically insignificant.

A bootstrap test confirms that the difference in peer effects between the two groups is statistically significant, with an empirical p-value of 0.091 (10 % level). These results suggest that left-behind children are more strongly affected by their peers' academic performance compared to their non-left-behind counterparts.

5. Heterogeneous peer effects

Table 6 reports heterogeneity in peer effects on math achievement, disaggregated by gender, boarding status, and baseline academic performance. Across all subgroups, left-behind children generally show stronger responses to peer academic influence than non-left-behind children.

Panel A reports gender differences. Among left-behind children, peer effects are significant for girls, indicating heightened sensitive of peer academic environments—possibly due to greater social sensitivity and relational orientation (Eagly & Wood, 1999; Rose & Rudolph, 2006). In contrast, peer effects for left-behind boys are smaller and statistically insignificant. For non-left-behind children, peer effects are negligible for both genders.

[5] The procedure is as follows: (1) assume that the number of left-behind children and non-left-behind children in the sample of n students is n1 and n2, respectively; (2) randomly select n1 and n2 student samples from the total n students and designate them as the left-behind children group and the non-left-behind children group, respectively; (3) estimate the coefficient values separately for the two groups and record the differences as di; (4) repeat steps 2 for 3k times ($k = 1000$ in this paper) and then calculate the percentage of di ($i = 1, 2, \ldots, k$) that is greater than the actual coefficient difference d0. This percentage represents the empirical p-value, which has the same meaning as the p-value in traditional tests.

[6] This study used the bootstrap method to test the difference in peer effects between left-behind children and non-left-behind children. The resulting empirical p-value of 0.478 suggests that the original hypothesis cannot be rejected, indicating no significant difference in peer effects between the two groups.

Table 3
Descriptive statistical analysis of variables between Non-left-behind children and Left-behind children.

Variables	Non-left-behind children		Left-behind children		Means test (P-values)
	Mean	SD	Mean	SD	
Student Academic Performance					
Standardized math scores	0.037	0.027	-0.035	0.028	0.071*
Standardized math scores (lag period)	0.019	0.028	-0.018	0.027	0.037
Peer academic performance and characteristics					
Average standardized math scores	0.168	0.017	0.085	0.018	0.083***
Average standardized math scores (lag period)	0.132	0.017	0.076	0.017	0.055**
Number of peers	4.411	0.029	4.374	0.029	0.037
Education of peer fathers (in years)	9.697	0.056	9.336	0.052	0.361***
Education of peer mothers (in years)	9.723	0.065	9.184	0.061	0.539***
Personal and Family Characteristics of Students					
Age (in years)	9.996	0.038	9.998	0.039	-0.002
Female (1=female, 0=male)	0.493	0.014	0.471	0.014	0.023
Boarding (1=yes, 0=no)	0.074	0.007	0.097	0.008	-0.022**
Father's education (in years)	9.495	0.095	9.238	0.091	0.257*
Mother's education (in years)	9.611	0.105	8.988	0.101	0.624***
Family Assets	0.157	0.033	-0.172	0.030	0.329***

Note: *, **, and *** denote significance levels at 10 %, 5 %, and 1 %, respectively; the last column shows the test of mean differences for the corresponding characteristics of left-behind children and non-left-behind children. Data source: Author's survey.

Panel B explores heterogeneity by boarding status. Non-boarding left-behind children are significantly influenced by peer achievement, while no significant effect is observed for boarding students. This may reflect the greater opportunity for informal peer interactions among non-boarders, which are conducive to peer influence (Kindermann, 2007; Ryan, 2001).

Panel C examines heterogeneity by baseline academic performance, dividing students into low, moderate, and high performance based on initial math scores. Peer effects are significant only among left-behind children with moderate academic performance, while effects are insignificant for those with low or high performance. For non-left-behind children, only the low-performing group shows a marginally significant effect. This pattern aligns with prior research suggesting that students with moderate achievement are most responsive to peer influence due to their motivation and capacity to improve (Wentzel & Watkins, 2002; Zimmerman, 2000).

Taken together, the findings highlight substantial heterogeneity in peer effects, with stronger impacts among left-behind girls, non-boarding students, and those with moderate academic performance.

6. Robustness tests

6.1. Lagged peer scores

To strengthen the reliability of our findings, we conduct a robustness test using lagged peer achievements as the main explanatory variable. Specifically, we use the average standardized math scores of peers from the previous period. This measure reflects peer ability at the beginning of the school year and is not influenced by the current students' scores, thus helping to mitigate concerns about reflection problem.

Table 7 reports the results of this robustness check. Columns (1) and (3) present OLS estimates, while Columns (2) and (4) report 2SLS results. For left-behind children, a one standard deviation increase in lagged peer math scores is associated with a 0.223 standard deviation increase in their own math scores ($p < 0.01$). For non-left-behind children, the corresponding effect is 0.178 standard deviation increase ($p < 0.01$). In the 2SLS regressions, the peer effect remains large and significant for left-behind children (0.719 SD, $p < 0.05$), but becomes statistically insignificant for none-left-behind children. These results reinforce the finding that peer effects are stronger among left-behind children.

6.2. Different best friend grades

We further test the robustness of our results by examining whether the academic performance of students' self-nominated first, second, and third best friends has different effects. We perform both OLS and 2SLS regressions using peer math scores, instrumented by the mean years of education of peers' fathers and mothers.

As shown in Table 8, for left-behind children, the math scores of both the first- and second-best friends have significant positive effects on individual performance. Specifically, the first best friend's score is associated with a 0.808 SD increase ($p < 0.05$), and the second-best friend's score with a 0.535 SD increase ($p < 0.05$). The third best friend's influence is positive but not statistically significant. In contrast, none of the three best friends' scores significantly affect non-left-behind children. These results indicate that left-behind children are more susceptible to peer academic influence, especially from their closest peers.

Table 4
OLS estimates of the effect of peer mean standardized math scores on individual standardized math scores.

Independent Variables	Dependent Variable: standardized math scores		
	Full sample (1)	Left-behind children (2)	Non-left-behind children (3)
Peer average standardized math scores	0.164***	0.162***	0.164***
	(0.034)	(0.049)	(0.048)
Number of peers (pcs)	-0.007	-0.008	-0.012
	(0.016)	(0.023)	(0.022)
Lag period standardized math scores	0.502***	0.512***	0.497***
	(0.017)	(0.025)	(0.023)
Student age (in years)	-0.165***	-0.182***	-0.140***
	(0.026)	(0.038)	(0.036)
Student gender (1=female, 0=male)	-0.044	-0.050	-0.022
	(0.031)	(0.045)	(0.043)
Boarding status (1=boarding, 0=not boarding)	-0.055	-0.051	-0.039
	(0.059)	(0.082)	(0.087)
Father's education (in years)	0.005	0.007	0.002
	(0.005)	(0.008)	(0.008)
Mother's education (in years)	0.006	0.005	0.009
	(0.005)	(0.007)	(0.008)
Left-behind children (1=yes, 0=no)	-0.003		
	(0.032)		
Family Assets	-0.015	-0.038	0.005
	(0.017)	(0.025)	(0.024)
Math teacher's teaching experience (in years)	-0.013	-0.011	-0.013
	(0.009)	(0.012)	(0.014)
Math teacher's gender (1=female, 0=male)	0.041	-0.069	0.118
	(0.110)	(0.138)	(0.193)
Math teacher's education (1=college and above, 0=below college)	-0.018	-0.130	0.062
	(0.081)	(0.125)	(0.108)
Math teacher's title (1=level 2 above, 0=level 2 and below)	0.055	-0.001	0.088
	(0.097)	(0.139)	(0.140)
Class size (number of students)	0.002	-0.000	0.003
	(0.007)	(0.013)	(0.009)
Fourth Grade	-1.009***	-0.280	-0.534
	(0.357)	(0.720)	(0.489)
Fifth Grade	-0.262	-0.064	0.702
	(0.387)	(1.041)	(0.668)
Sixth Grade	-0.058	-0.530	-0.745
	(0.339)	(1.153)	(0.609)
Constant	2.395***	2.017*	1.502***
	(0.436)	(1.221)	(0.473)
School fixed effect	Yes	Yes	Yes
Observations	2604	1313	1291
P-value		0.478	
R-squared	0.435	0.450	0.447

Note: *, **, and *** denote 10 %, 5 %, and 1 % significance levels, respectively.
Data source: Author's survey.

6.3. "Placebo" test

While this study controls for observable factors at the school and classroom levels—both known to influence student achievement—it is important to acknowledge that unobservable factors may still bias the estimated peer effects. To address this concern, we implement an indirect placebo test, a method widely used in the literature (Ferrara et al., 2012; Song et al., 2019).

According to Eqs. (2) and (3), the estimated peer effect coefficient $\widehat{\beta}_1$ can be expressed as:

$$\widehat{\beta}_1 = \beta_1 + \frac{COV\ (\ Z\ ,\ U|W\ )}{COV\ (\ Z\ ,\ X|W\ )}$$

Here, W contains the full set of control variables and fixed effects; X are the endogenous explanatory variable (peer achievement); Z is a vector of instrumental variables (i.e., years of education of peer parents); and $COV(Z\ ,\ U|W)$ represents the correlation between unobservables and instrumental variables. Because it is impossible to verify directly that $COV(Z\ ,\ U|W)\ = 0$, which indicates unbiased estimation of $\widehat{\beta}_1$, we employ a proxy-based approach to test instrument validity.

Specifically, we randomly assign each student a "dummy peer" drawn from another school within the same county. We then use the dummy peer's parental education as an instrument for the dummy peer's math achievement in a 2SLS regression. This process is then repeated 300 times to generate a distribution of $\widehat{\beta}_1^{\,random}$.

Table 5
Results of 2SLS estimates of the effect of mean peer math scores on individual standardized math scores.

Independent variables	Dependent variable: standardized math scores					
	First-stage regression results			Second-stage regression results		
	Full sample	Left-behind children	Non-left-behind children	Full sample	Left-behind children	Non-left-behind children
	(1)	(2)	(3)	(4)	(5)	(6)
Peer mean standardized math scores				0.359*	0.678**	0.135
				(0.186)	(0.310)	(0.230)
Average years of education of peer fathers (years)	0.032***	0.036***	0.026***			
	(0.007)	(0.009)	(0.010)			
Average years of education of peer mothers (years)	0.027***	0.017**	0.040***			
	(0.006)	(0.009)	(0.009)			
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Under-identification test (p-value)	0.00	0.00	0.00			
Weak instrumental variable test (Cragg-Donald Wald F statistic)	41.55	16.21	25.85			
Over-identification test (p-value)	0.34	0.39	0.73			
P-value					0.091	
Sample size	2604	1313	1291	2604	1313	1291

Note: *, **, and *** denote 10 %, 5 %, and 1 % significance levels, respectively.
Data source: Author's survey

Table 6
Heterogeneity in the effect of mean peer math scores on individual math test scores.

		Left-behind children (1)	Non-left-behind children (2)
Panel A			
Female	OLS	0.138*	0.077
		(0.081)	(0.078)
	IV	0.788**	0.015
		(0.388)	(0.397)
Male	OLS	0.069	0.076
		(0.067)	(0.068)
	IV	0.700	-0.168
		(0.601)	(0.354)
Panel B			
Boarding	OLS	-0.076	0.240
		(0.244)	(0.188)
	IV	1.777	0.430
		(1.888)	(0.443)
Non-boarding	OLS	0.181***	0.157***
		(0.050)	(0.050)
	IV	0.678**	0.158
		(0.294)	(0.251)
Panel C			
Low academic performance	OLS	0.047	0.237***
		(0.081)	(0.085)
	IV	0.401	-0.013
		(0.592)	(0.375)
Moderate academic performance	OLS	0.360***	0.046
		(0.087)	(0.085)
	IV	0.994**	0.047
		(0.400)	(0.360)
High academic performance	OLS	0.147	0.219**
		(0.097)	(0.094)
	IV	0.254	0.916
		(0.514)	(0.693)

Note: *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. Standard errors are in parentheses. The dependent variable is the individual standardized math scores. The key independent variable is the peer average standardized math scores. Reported are the coefficients and standard errors of the independent variable. All regressions include control variables and school fixed effect. Panels A, B, and C report results by gender, boarding status, and academic performance, respectively. Students are grouped into low, moderate, and high academic performance quantiles based on baseline math test scores.
Data source: Author's survey.

Table 7
Robustness tests for the effect of mean peer math scores (lagged) on individual standardized math scores.

Independent variables	Dependent variable: standardized math scores			
	Left-behind children		Non-left-behind children	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Peer's lagged average math scores	0.223***	0.719**	0.178***	0.111
	(0.048)	(0.312)	(0.046)	(0.235)
Control variables	Yes	Yes	Yes	Yes
School fixed effect	Yes	Yes	Yes	Yes
R-squared	0.455	0.407	0.449	0.448
Sample size	1313	1313	1291	1291
Identification test		0.000		0.000
Weak instrumental variable test		15.30		22.82
Over-identification test		0.619		0.623

Note: *, **, and *** denote 10 %, 5 %, and 1 % significance levels, respectively.
Data source: Author's survey.

Fig. 1 illustrates the distributions of $\widehat{\beta}_1^{random}$ for the full sample, left-behind children, and non-left-behind children, respectively. The vertical solid lines represent the "correct" estimated coefficients (i.e., the IV coefficients in Table 4). The point estimate is the coefficient magnitude for each regression, while the solid line is the fitted coefficient distribution. Upon examining the distributions for the full sample and left-behind children, it is evident that $\widehat{\beta}_1^{random}$ of both groups are centered around zero, in accordance with the expectations of the placebo test. This implies that the "dummy peers" do not have a significant effect on academic performance for either group, as indicated by the absence of notable deviations in the distributions.

7. Mechanisms

Table 9 presents the mechanism analysis examining how peer academic achievement affects students through changes in attitudes and behaviors related to mathematics—such as perceived value of effort, academic stress, comprehension, fear of failure, and homework completion. Columns 1–2 report the effect of peer achievement on a composite mechanism index of six intermediate variables, constructed using Principal Component Analysis (PCA). Columns 3–14 present results by individual dimensions, allowing for a more nuanced understanding of the mechanisms at work.

The PCA-based results indicate that peer average achievement is positively associated with the composite mechanism index for both groups. However, only the coefficient for left-behind children is substantively large (0.250), while the effect for non-left-behind children is small and negative (–0.045); neither estimate reaches statistical significance.

Turning to the disaggregated results, left-behind children exhibit statistically significant improvements across several individual dimensions. Specifically, they are more likely to believe that effort in mathematics is worthwhile (Column 3, OLS coefficient = 0.017, $p < 0.1$), exhibit greater confidence in handling difficult math problems (Column 9), and demonstrate higher rates of homework completion (Column 13), with the latter being particularly strong and significant in the IV specification (0.363, $p < 0.05$). Other estimated peer effects for left-behind children, although not statistically significant, are consistently positive, such as increased perception of the importance of math for future development (Column 5), reduced academic stress (Column 7), and lower levels of anxiety about poor performance (Column 11).

In contrast, peer effects for non-left-behind children are generally small, statistically insignificant, and inconsistent in direction. While some coefficients are positive—such as those for effort, comprehension, and homework—others are negative, including academic stress and fear of failure. None of these effects reach conventional significance threshold.

Overall, the findings suggest that peer academic achievement influences students primarily by shaping their attitudes toward mathematics, enhancing their learning confidence, and improving study habits, particularly among left-behind children.

8. Discussion and conclusion

Rural children are a vital component of China's future human capital, and left-behind children—those separated from their parents due to labor migration—represent a significant and often vulnerable segment of this population. Improving their academic outcomes is essential for promoting equity and long-term rural development.

Among the various factors influencing left-behind children, the peer effect holds particular significance. This paper examines the role of peer effects in shaping the mathematics achievement of left-behind children. Using an instrumental variable approach, we analyze data from 2604 students in grades three to six across 60 elementary schools in rural western China. We also investigate variations in peer effects between left-behind and their non-left-behind counterparts by sub-sample analysis.

Our findings yield several key insights. Firstly, peer effects have a significant and positive influence on students' math performance. A one standard deviation increase in peer achievement is associated with a 0.359 standard deviation improvement in a student's own math score. These results align with prior findings, such as Min et al. (2019) on rural migrant children in urban China and Carman and

Table 8
Robustness tests for the effect of first, second and third peer math scores on individual standardized math scores.

Independent variables	Dependent variable: standardized math scores											
	Left-behind children		Non-left-behind children		Left-behind children		Non-left-behind children		Left-behind children		Non-left-behind children	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
The first friend math score	0.059**	0.808**	0.061**	0.112	0.052*	0.016	0.057**	0.055**	0.056**	0.080**	0.065**	0.061**
	(0.026)	(0.406)	(0.025)	(0.188)	(0.027)	(0.034)	(0.025)	(0.025)	(0.028)	(0.039)	(0.026)	(0.027)
The second friend math score					0.030	0.535**	0.059**	0.228	0.027	0.027	0.033	0.028
					(0.025)	(0.230)	(0.025)	(0.220)	(0.026)	(0.033)	(0.026)	(0.027)
The third friend math score									0.033	0.778	0.039	0.285
									(0.027)	(0.541)	(0.025)	(0.440)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
School fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.447	0.072	0.453	0.451	0.452	0.256	0.453	0.442	0.455	0.073	0.463	0.416
Sample size	1291	1291	1277	1277	1228	1228	1228	1228	1158	1158	1152	1152

Note: *, **, and *** denote 10 %, 5 %, and 1 % significance levels, respectively. To eliminate the confounding effect of the order of best friends, especially the influence of the preceding best friends on the subsequent ones, the first best friend's score is controlled when examining the impact of the second best friend's score on the outcome. Similarly, the regression of the third best friend also controls for the influence of the first and second best friends
Data source: Author's survey

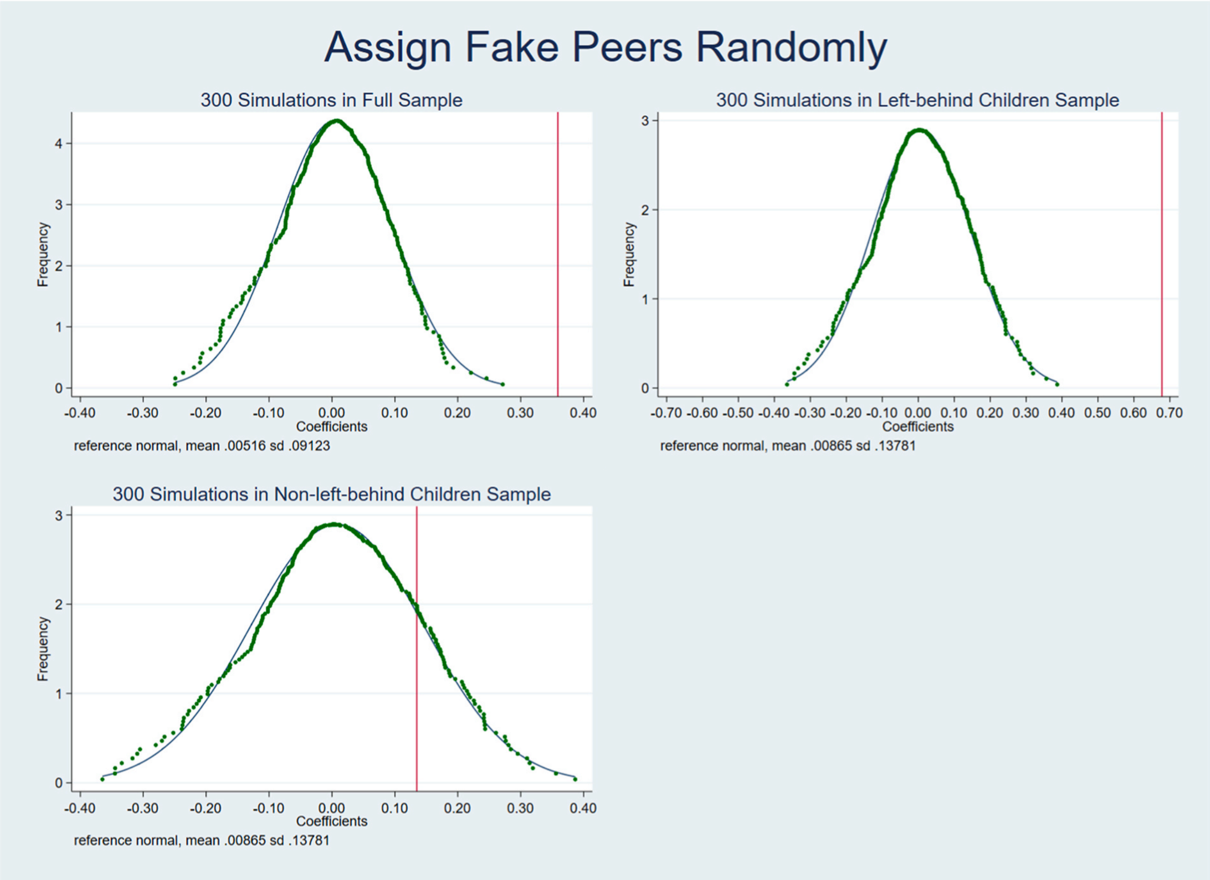

Fig. 1. Placebo test.

Zhang (2012) on U.S. students.

Secondly, left-behind children exhibited a higher susceptibility to the influence of their peers compared to non-left-behind children. For this group, a one standard deviation increase in peer math scores leads to a 0.678 standard deviation increase in their own scores, while the peer effect is statistically insignificant among non-left-behind children. These findings underscore the importance of peer influence in the academic achievement of rural students, particularly among left-behind children. Additionally, the academic influence of the first- and second-best friends is particularly strong for left-behind children, highlighting the critical role of close peer relationships. Heterogeneity analysis further shows that peer influence is especially pronounced among left-behind girls, non-boarding students, and those with moderate baseline academic performance.

Why are left-behind children more affected by their peers? The mechanism analysis reveals that their limited parental academic support makes them more reliant on peers for academic guidance. Peer interactions appear to enhance their attitudes toward mathematics, build confidence, and improve study habits—three key pathways through which peer influence translates into improved academic performance.

These findings carry important policy implications. Firstly, it is evident that both the family environment and school resources influence students' academic performance. For left-behind children, who often experience a lack of emotional communication and academic guidance within their family environment, the school environment may serve as a compensatory factor. Access to school resources and peer communication allows left-behind children to bridge gaps in their family environment, providing them with the necessary support and guidance, ultimately resulting in a positive impact on their academic performance. Recognizing the potential of peer communication, educators can play a crucial role in addressing the specific needs of left-behind children and creating a more supportive and conducive learning environment with peers for their academic development.

Secondly, teachers should take into account the influence of peer effects on left-behind children when making classroom seating arrangements. Considering students' academic performance as one of the factors, teachers can optimize peer interactions to harness the positive impact of peer effects on left-behind children.

We acknowledge one key limitation of this study: our data collection did not provide sufficient information and variables to fully explore the underlying mechanisms. While we attempted to identify the causal effect of peers on left-behind children, we cannot definitively analyze the mechanism through which this occurs. Future research should utilize longitudinal dynamic panel designs to better understand how peer interactions develop and affect academic outcomes over time.

Table 9
Mechanism analysis by left-behind status.

	Dependent variables					
	Overall mathematics learning performance		It is worthwhile to make efforts in mathematics, as it will benefit my future.		Learning mathematics is important for me because it enhances my future professional capabilities.	
	(1) Left-behind children	(2) Non-left-behind children	(3) Left-behind children	(4) Non-left-behind children	(5) Left-behind children	(6) Non-left-behind children
OLS	0.057	-0.032	0.017*	0.009	0.009	0.004
	(0.035)	(0.034)	(0.010)	(0.009)	(0.016)	(0.015)
IV	0.250	-0.045	0.030	0.021	0.086	0.084
	(0.214)	(0.157)	(0.060)	(0.041)	(0.093)	(0.071)

	Dependent Variables							
	I do not feel very stressed when doing math assignments.		I can comprehend even the most challenging content in math class.		I am not concerned about poor performance in mathematics in the future.		The frequency of my math homework submissions.	
	(7) Left-behind children	(8) Non-left-behind children	(9) Left-behind children	(10) Non-left-behind children	(11) Left-behind children	(12) Non-left-behind children	(13) Left-behind children	(14) Non-left-behind children
OLS	0.049*	0.038	0.068**	0.012	0.066**	0.012	0.032	-0.029
	(0.026)	(0.026)	(0.028)	(0.028)	(0.028)	(0.028)	(0.025)	(0.025)
IV	-0.047	0.002	0.454**	0.126	-0.239	-0.025	0.363**	0.069
	(0.157)	(0.123)	(0.177)	(0.128)	(0.175)	(0.129)	(0.155)	(0.114)

Note: *, **, and *** denote 10 %, 5 %, and 1 % significance levels, respectively. Reported estimates are obtained from ordinary least squares (OLS) and two-stage least squares (2SLS) regressions, respectively. In column (1) and (2), the dependent variable is the standardized score of overall mathematics learning performance, constructed using principal component analysis (PCA) based on six indicators. The dependent variables in columns (3) through (14) are binary indicators that describe specific aspects, taking a value of 1 if the behavior is always present and 0 if it seldom or never occurs. The independent variable is peer average standardized math scores. Coefficients and standard errors of independent variables are shown. All regressions include control variables and school fixed effect."

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CRediT authorship contribution statement

Yi Zhang: Software, Methodology, Investigation, Formal analysis, Data curation. **Fang Chang:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yanan Huo:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Songyan Zhang:** Writing – original draft, Visualization, Validation, Software, Investigation, Formal analysis, Data curation. **Yajie Wang:** Validation, Software, Methodology, Formal analysis, Data curation. **Jian Liu:** Software, Investigation, Formal analysis, Data curation.

Declaration of Competing Interest

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