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# School Quality and Peer Effects: Explaining Differences in Academic Performance between China's Migrant and Rural Students

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ABSTRACT *In China, parents have a choice to either send their children to private migrant schools in urban areas or to keep them in their own county. It is unclear whether the academic differences of students in rural schools and those in private migrant schools is due to the quality of schools, the quality of students/peers, or the ways that peer effects interact with the quality of the school. Using survey data from students with rural residency who attended either migrant schools or rural public schools, we measure how differences in the quality of the types of schools and how the effect of peers differs in high- versus low-quality schools. An instrumental variable approach is used to identify the causality of a student's peers on his or her academic outcomes and within the context of each of the school venues. The gap in student academic performance is explained by the differences in each student's peers as and in how peers interact in the schooling environments. The analysis also demonstrates that there is a significant interaction effect between one's peers and the quality of a student's school environment. We found that school quality has a complementary effect with peers on student academic performance.*

## 1. Introduction

In China, parents who have their residency in rural areas but who work in urban areas need to decide whether to send their children to private migrant schools in urban areas or have them remain in rural areas and attend local public schools (Zhao, Yu, Wang, & Glauben, 2014). When parents decide to bring their children with them to the city, their *migrant children* are almost always educated in schools with other migrant children but not urban children, which we refer to as *private migrant schools*. The literature has documented the general conditions of these schools for migrant children (Goodburn, 2009; Lai et al., 2014) and that teacher turnover is high (Wang, Luo, Zhang, & Rozelle, 2017).

In contrast, if parents decide to have their children stay in their home county, their *rural children* will attend *rural public schools*. Although, historically, the quality of rural schools was not high (Zhang, Jin, Torero, & Li, 2018), in recent years, the government has undertaken a systematic effort to improve the quality of the educational infrastructure in many rural areas

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(Chen, 2015). Teacher absenteeism has become relatively low, and there is a system in place to ensure that teachers are focused on teaching a standard, approved curriculum. Further, public education policy stipulates that all teachers must now have a minimum level of education and certification (Chen & Feng, 2013), and this has led to a decrease in the rate of teacher turnover (Lai, Sadoulet, & de Janvry, 2011). Facilities in rural public schools also have improved due to recent large, centrally funded fiscal investments (Mo et al., 2020).

Although the exact source of the differential is not known, there is a consensus in the literature that the performance of rural students is better than that of migrant students. Ma et al. (2018) find that the scores on a standardised maths test taken by students who attend rural public elementary schools in two Northwestern provinces are significantly higher than those of students who attend private migrant schools. Using a dataset that matched migrant students from the greater Shanghai area with rural students who were attending rural public schools in the communities from which the families of the migrant students came, Wang et al. (2017) also found higher standardised test scores for the rural students. Using the scores of migrant students from Beijing and rural students from Shaanxi and Gansu provinces, Lai et al. (2014) demonstrated how rural students in their sample of rural public schools performed better than those included in the sample of migrant students.

One potential reason for the differences between rural and migrant students is that the quality of rural public schools is better, on average, than that of private migrant schools. The literature empirically demonstrates that school quality strongly determines student performance (Angrist & Lang, 2004; Chen & Feng, 2013; Ding & Lehrer, 2007; Lai et al., 2011; McEwan, 2003). Moreover, previous studies have found that the quality of private migrant schools is relatively low compared to that of urban public schools (Chen & Feng, 2013) and rural public schools (Wang et al., 2017). For instance, Wang et al.'s study investigated the cause of the academic gap between the students in private migrant schools and those in the rural public schools and found that a large part of the gap was due to observable differences in school quality, including the qualifications of teachers and the facilities of the schools. Further, Lai et al. (2014) presented empirical evidence that the longer that students spent in private migrant schools, the worse that the students performed (as compared to the performance of students in rural public schools).

Another potential cause of the discrepancy in performance of migrant and rural students may be that parents decide to take different types of students into the city relative to those who are left behind. To our knowledge, no previous research has considered the question of whether migrant children or rural students tend to have individual or family characteristics that, at least in part, explain the rural-migrant schooling performance gap. The education literature, however, is replete with examples of how families with more resources, both financial and human capital, will choose the schooling options, including taking into consideration the quality of the peers with whom their children will go to school and interact. There also is research that shows that families with stronger financial backgrounds are able to choose premiere, private prep schools in the United States (Abdulkadiroğlu, Pathak, & Roth, 2005; Angrist & Lang, 2004; Dobbie & Fryer, 2014). Research teams in different countries (for example South Korea: Kim, Lee, & Lee, 2008; China: Park, Shi, Hsieh, & An, 2015) also have documented how families purposively move into public school districts that have higher-quality schools and student body.

Given these differences in school quality between migrant and rural schools, it also is possible that the nature of one's peers may affect the ability of children to learn. A common hypothesis is that student outcomes will improve if students attend a school with higher-performing peers. Indeed, research demonstrates empirically that student outcomes are higher when students have positive interactions with higher-performing peers (Hanushek, Kain, Markman, & Rivkin, 2003; Hoxby, 2000; Kang, 2007; McEwan, 2003; Winston & Zimmerman, 2003). The factors that affect an individual's learning (for example the quality of the school environment, including teachers and physical facilities) also could interact indirectly with those of their peers, leading to peer effects that can be considered a social multiplier effect (Entorf & Lauk, 2008; Koedel, Mihaly, & Rockoff, 2015). If this multiplier effect is sufficiently strong, this also may mean that peer effects are stronger in schools that are of high quality, which may help to account for another dimension of the differences in performance that have been observed to exist between migrant and rural students.

In this paper, we examine several hypotheses. First, school quality is an important correlate of the differences observed between migrant and rural students. Second, peer effects are important determinants of differences in schooling outcomes. Finally, in schools that are of higher quality, peer effects are amplified. The overall goal of our study is to test these hypotheses as a way to explain the differences in the academic performance of migrant and rural students.

One of the most important reasons for the absence of empirical evidence on the fundamental issue of why students in private migrant schools systematically underperform, even relative to students in rural public schools, is the lack of quantitative and comparable data on both types of schools. In our study, we collected data on 87 private migrant schools in Shanghai and Suzhou and 30 rural public schools in Anhui (in the home communities of a large share of the sample migrant students). Comparisons between migrant and rural students, using researcher-collected primary data and including outcomes from a timed standardised maths test proctored by the survey team, allow us to determine the sources of the differences in the academic performance of students in regard to whether it is due to the quality of the schools, differences in peer effects, or some combination thereof.

Using these data, we use our benchmark multivariable model, an ordinary least squares (OLS) model that uses educational outcomes from the standardised maths test at the student level, as the dependent variable. We also can measure the association of each student's outcomes with those of his or her peers, the students who study and socialise together in class, while controlling for all of the observables of the student (Lyle, 2007).

In our effort to identify the causal effects of one's peers on the academic outcomes of each sample student, we use the educational attainment levels of each of the parents of each student's closest peer as an instrumental variable, or IV (Angrist, 2014). We conclude that the levels of educational attainment of the parents of a peer are valid IVs, as the variable can influence the outcomes of the peer but are unrelated to other unobservable individual characteristics that might influence student performance. In addition to logically meeting the requirements of an IV, statistical tests find the IVs to meet the statistical requirements of valid instruments. We also use heterogeneous analysis to measure whether peer effects are stronger or weaker in schools that are of higher quality.

Our findings indicate that, as is seen in other studies, students in rural public schools performed better than did those in private migrant schools. The raw difference shows that rural students scored 1.11 standard deviations (SDs) higher than did migrant students. Based on the results of the IV analysis, and after considering peer effects (+0.161 SDs), the conditional impact of school quality (holding observed school quality and student characteristics constant) in explaining the difference in academic performance between migrant and rural students fell to 0.285 SDs. The difference fell further to 0.273 SDs when we included a variable that interacted peer effects with school quality.

With regard to the difference in peer effects in migrant and rural schools, the results showed that peer effects in rural schools are systematically higher (0.443 SDs in rural schools versus 0.042 SDs in migrant schools). Overall, the results also suggest that student outcomes are higher when students positively interact with higher-performing peers in a better-quality school.

The remainder of the paper is organised as follows. Section 2 presents the sampling and data source. Section 3 presents the theoretical concept and empirical estimation strategies. Section 4 reports the descriptive analysis and the results from the multivariate analysis without and with IV estimation strategies and the robustness checks. Section 5 provides a discussion of the findings and concludes.

## 2. Sampling and data source

### *2.1. Sampling*

We used the following sampling strategy to collect the data used in the study. We began by conducting a canvass-like survey to choose a sample of schools in two suburban areas around Suzhou, Jiangsu Province, and Shanghai's outlying districts and counties. A total of 87 schools were chosen. To further select the sample, in each of the private migrant schools, we randomly chose one fifth grade class. In total, there were 3,188 migrant students in 87 fifth grade classes in 87 private migrant schools.

In the initial canvass survey that we conducted, we asked sample students to identify the community (by prefecture name) from which they (or their parents) came. Of the 3,188 fifth grade students in the private migrant school sample, one-fourth ($n$ = 788) came from three prefectures in Anhui Province: Fuyang, Lu'an, and Bozhou. In the remainder of this paper, we will refer to these three prefectures as the three *rural study areas*. We chose two counties each in Fuyang and Lu'an prefectures and one county in Bozhou prefecture. The counties were randomly chosen from the list of counties in each prefecture. We randomly selected six schools in each county. In total, we selected 30 rural public schools.

We focused on all of the students in one randomly chosen fifth grade class in each of the rural public schools. A total of 1,480 rural students were included in our sample of 30 schools in five counties in Anhui Province. On average, there were 50 fifth grade students per class in our rural public schools. As seen in Table 1, when put together with the migrant students from the private migrant schools, the *overall sample* (Dataset 1) included 4,668 students (3,188 migrant students and 1,480 rural students).

From this overall sample, we also identified the subsample of rural students who were from the same source communities as the migrants. This was done as part of our attempt to minimise the importance of unobservables that might differ between migrant and rural students and affect the comparisons that the analysis will be measuring. Of the 3,188 fifth grade students in the private migrant school, 788 migrant students came from three prefectures in Anhui Province (Table 1). This subsample ($n$ = 2,268) combines the 788 migrant students in private migrant schools and the 1,480 rural students in rural public schools. This subsample, defined as the *geographically matched subsample* (Dataset 2), is used for the robustness check of the main results.

### *2.2. Data source*

In each of the samples of private migrant and rural public schools, teams of enumerators carried out the survey, which consisted of four blocks. The first block is a school-level survey that

**Table 1.** Sample sizes of the datasets

| | | Number of students | | | | |
|---|---|---|---|---|---|---|
| | | | Private migrant schools | | | Rural public schools |
| Dataset | Description | Total | Shanghai & Suzhou | Shanghai | Suzhou | Anhui |
| 1 | Overall sample | 4,668 | 3,188 | 2,289 | 899 | 1,480 |
| 2 | Geographically matched subsample | 2,268 | 788 | 628 | 160 | 1,480 |

collected information about school characteristics, the quality of the teaching staff, and the school's history. The second block of questions are designed to collect the information of teachers including the ranking, gender, age and major. To execute the third block of the survey, the enumerators conducted a student survey, in part, to measure the characteristics of the students and their families. Each student was asked the question about his or her peers. The objective of the question was to identify, in the same class, the person with whom each student most frequently got together to study. In our survey, a peer was defined as a student's main *learning companion*. This definition is similar to that used in research by Lyle (2007), Merlino, Steinhardt, and Wren-Lewis (2019), and Min, Yuan, Wang, and Hou (2019). More precisely, learning companions are pairs of students who most frequently get together to discuss questions about the lectures, work together on their homework, or, in some cases, take tutorials together. Learning companions also are those who most frequently exchange class text books or extracurricular reading books.[1] In the remainder of the paper, we refer to this primary learning companion as *peer*.

In the fourth survey block, our measure of student academic performance is each student's score on a fifth grade-specific, standardised mathematics test. These tests were designed specifically to be appropriate for rural students in the fifth grade, that is students were tested on their maths curriculum. The tests were administered on paper, and the examination was timed (25 minutes) and closely proctored by the research team's enumerators at each school.

## 3. Methodology

### 3.1. Conceptual framework

A student's academic achievement can be modelled as an educational production function (Hanushek, 1979; Henderson, Mieszkowski, & Sauvageau, 1978; Polachek & Harwood, 1978; Robertson & Symons, 2003). In the educational production function, student's achievement is found to depend on inputs of individual, family, school, teacher, class and peer group (Ding & Lehrer, 2007; Feng & Li, 2016; Koedel et al., 2015; Marotta, 2017; Sacerdote, 2011; Sass, Semykina, & Harris, 2014). This can be applied to analyse the academic performance of rural students who studied either in private migrant schools or rural public schools. The studies found that the quality of schools played a significant role in explaining the gap in schooling outcomes between migrant students and rural/urban students after controlling for the characteristics of individual, family, school, teacher and class (Chen & Feng, 2013; Lai et al., 2014; Wang et al., 2017). Nevertheless, these studies neglected the peer effects.

While peer effects on a student's academic performance are heterogeneous among different schools (Griffith & Rask, 2014; Min et al., 2019; Zimmer & Toma, 2000), it remains unclear to what extent peer effect contributes to the educational gaps between students in private migrant and rural public schools. Previous studies show that if the unobserved inputs at the school level are controlled for, the estimated peer effects will become weaker (Kang, 2007), implying peer effects may vary with the school quality. In other words, peer effects themselves may be influenced by the characteristics of schools. In such a case, even though the peer effect is further taken into account in the model that aims to explain the schooling outcome gaps of students between these private migrant schools and rural public schools, the estimates of peer effects may also be inconsistent and biased. To further focus on the interaction between school quality and peer effects, we use the following typical form of a student achievement function:

$$y_{ics} = f(S_i, P_i, X_i, F_i, T_i) \tag{1}$$

where $y_{ics}$ is the standardised maths test score of the student $i$ in class $c$, school $s$; $S_i, P_i, X_i, F_i, T_i$ represent vectors of school, peer, student, family and teacher characteristics, respectively. Note, in the empirical estimation framework, we allow the interaction between school quality and peer effects.

### 3.2. Empirical estimation strategies

The overall empirical strategy are threefold. In the first part of the analysis, we look at the raw differences in the academic performance of peers in migrant and rural schools. In the second part of the analysis, which also is correlative, we use OLS regression analysis to examine the differences in the performance of students from migrant and rural schools. We start with an initial simple OLS regression that measures the raw difference (measured in SDs) between migrant and rural students. Next, we add the variables of observed school/teacher and student/family characteristics to determine the extent to which the difference in the scores of migrant and rural students is still explained by the migrant school variable. In the following step of the analysis, we add the variable as a measure for the nature of each student's peer. This allows us to generate the first empirical (although not causal) evidence of the importance of school quality. We include an interaction term between the quality of a student's peer and his or her school type (private migrant or rural public) in an effort to understand the extent to which the size of the peer effects are influenced by the quality of the schools that students attend.

In the third part of the analysis, we focus on identifying the causal relationship between one's peer and one's academic performance. In this analysis, we use an IV approach, seeking to produce a well-identified measure of the relationship of interest. After we demonstrate that the IV meets the requirements of a valid instrument, we repeat the analysis, using the same logic as the OLS analysis but, this time, with the aim to identify causal effects of student peers to explain part of the difference between the academic performance of students in migrant and rural schools.

*3.2.1. Multiple regression analysis.* To estimate the associations between peers and school quality and student academic achievement (as well as an interaction effect), a multiple regression model is established, as seen in the following equation, by controlling for teacher, school and student/family characteristics that could affect student performance:

$$y_{ics} = \beta_0 + \beta_1 mig_s + \beta_2 peer_{ics} + \beta_3 mig_{\mathrm{s}} \times peer_{ics} + \beta_4 T_{cs} + \beta_5 S_s + \beta_6 X_{ics} + \varepsilon_{ics} \tag{2}$$

where $y_{ics}$ is the standardised maths test score of the student $i$ in class $c$, school $s$; $mig_s$is a dummy variable that is 1 for migrant students and 0 for rural students; $peer_{\mathrm{ics}}$ is the standardised maths test score of peer $i$ in the same class $c$, school $s$ who is the peer of the student $i$ in class $c$, school $s$; and $mig_s \times peer_{ics}$ measures the interaction between $mig_s$ and $peer_{ics}$. Here, $T_{cs}$ and $S_s$are a vector of observable variables that measure characteristics of the home teacher and school quality in class $c$, school $s$, respectively; and $X_{ics}$ is a vector of the student and family characteristics of student $i$. We also use the school fixed effects in the estimations to control for non-time varying unobservables. $\varepsilon_{ics}$ is idiosyncratic error term.

Based on the discussion above, the main coefficients of interest are $\beta_1$, $\beta_2$, and $\beta_3$. Note that the specification allows the peer effect to differ at the different types of school (private migrant schools and rural public schools) by inclusion of an interaction term. Specifically, $\beta_2$is the average effect of the peer's score on the students in the rural public school; $\beta_2 + \beta_3$ measures the average effect of the peer's score on the students in the private migrant school; and $\beta_1 + \beta_3 \times peer_{ics}$ is equal to the conditional difference in mean of standardised test scores between the students in the migrant school and rural public school.

*3.2.2. Instrumental variable estimations.* As described above, we also are interested in moving beyond measuring correlations to assess the causal impact of a student's peer on the performance of the student. To address the possibility that endogeneity may affect the measurement of the relationship between the nature of one's peers and his or her academic performance, we use an IV approach. Research methods used in previous studies that seek to solve the endogeneity of a student's peer include randomised interventions (Li, Han, Zhang, & Rozelle, 2014; Ludwig, Hirschfeld, & Duncan, 2001), natural experiments (Winston & Zimmerman, 2003), or IVs (Kang, 2007). As the gold-standard method, randomised interventions are difficult to implement and normally involve high costs, whereas natural experiments are difficult to find in the real world (Min et al., 2019). Thus, the common methods in empirical studies are the use of IVs or fixed-effects models. In the case of our study areas, it is not possible to run a randomised controlled trial, and there is no natural experiment. Therefore, IVs is the only possibility for identifying the causality of the effect of a student's peer (and its interaction with school quality) on student academic performance, controlling for the school fixed effects.

In searching for a valid IV, we need a variable that will affect the academic performance of the peer but not have an impact on the student except through the peer. We use the levels of educational attainment of the parents of the peer as the IVs. We believe that a characteristic of the parents of the peer (which has a significant effect on the peer's academic outcome) can act as an IV because, as the literature shows (Bai et al., 2018), parents in China's rural areas and migrant communities have little contact with the children (or family of the children) who are in the schools of their own children. In addition, fertility rates in China today are so low that there are not many children who belong to the same age cohort in a village, and when two students do live in the same village, the distance between their households is typically quite large (which would minimise direct contact between a student and his or her peer's parents or between a student's parents and either the peer or the peer's parents). Therefore, the parents of the peer would be expected to have an impact on the peer's academic performance (through a number of channels, including the levels of education of the parents), which would mean that the first assumption of a valid IV is met. In addition, the absence of contact between the peer's friend and the peer's parents means that the entire impact of the peer's parents and the student is through the peer himself or herself, which would satisfy the second assumption of a valid IV.

The second-stage least-squares (2SLS) regression can be written as either:

$$y_{ics} = \delta_0' + \delta_1' mig_s + \delta_2' \widehat{peer}_{ics} + \delta_3' T_{cs} + \delta_4' S_s + \delta_5' X_{ics} + \varphi_{ics}' \tag{3}$$

or

$$y_{ics} = \delta_0 + \delta_1 mig_s + \delta_2 \widehat{peer}_{ics} + \delta_3 \widehat{peer}_{ics} \times mig_s + \delta_4 T_{cs} + \delta_5 S_s + \delta_6 X_{ics} + \varphi_{ics} \tag{4}$$

In Equations (3) and (4), the peer effect variable ($\widehat{peer}_{ics}$) and its interacted term with the school dummy are the predicted values of the variables from the first-stage estimations, respectively. In Equation (3), we seek to measure the causal impact of peer effects ($\widehat{peer}_{ics}$) on $y_{ics}$, the standardised maths test score of the student $i$ in class $c$, school $s$. In Equation (4), we add one variable by interacting $\widehat{peer}_{ics}$ with $mig_s$ to assess the differences of the peer effects in migrant and rural schools. The school fixed effects are also controlled in the two equations. In the first stage analysis, $fa\_edu_{ics}$ and $mo\_edu_{ics}$ the educational attainment of the peer's (the peer of student $i$ in the same class $c$, school $s$) father and mother, separately, are used as the IVs of the academic performance of the peer.

## 4. Results

### *4.1. Descriptive analysis*

Before presenting the results of multivariate empirical analysis, we undertake three sets of descriptive analyses. First, we examine the distributions of the test scores overall and among students in the different types of schools. Second, we conduct simple comparisons of test scores – migrant students versus rural public students – as well as compare the test scores of peers in the two types of schools.

### *4.2. Standardised test scores distributions and differences between types of schools*

It is important in the design of standardised maths tests that the distribution of the scores are normal and not subject to either ceiling effects (too many students earn perfect scores) or floor effects (too many students score zero or have very low scores). As can be seen in Figure 1, the distributions of the maths scores for the migrant students and rural public students appear to be nearly normal in their shape. In looking at the two distributions, it is clear that the average scores of rural students are considerably above those of migrant students, given that the distribution of rural student scores clearly lies to the right of the distribution of the migrant student scores.

The descriptive statistics of the maths scores quantify that there is a large (raw) educational gap between the students in the private migrant and rural public schools (Table 2). This is true of the

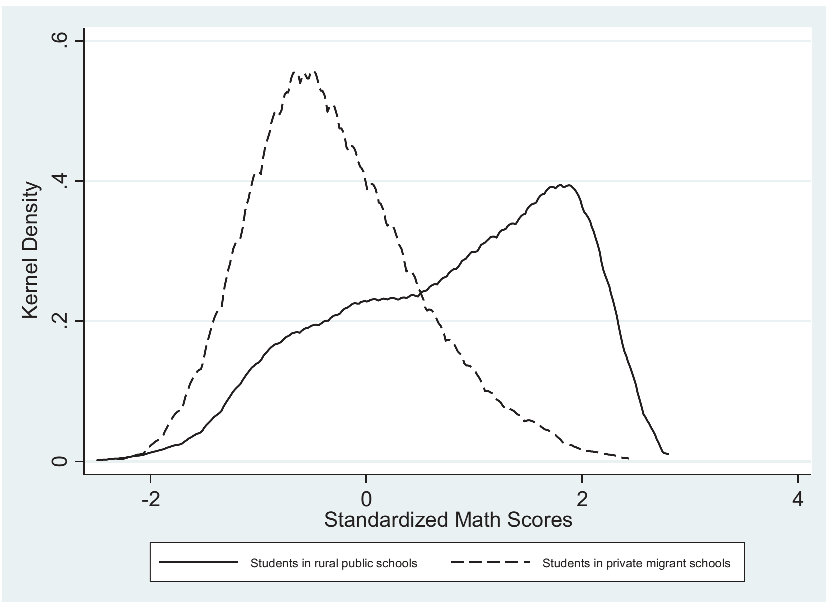


**Figure 1.** Kernel densities that show the distribution of student standardised maths scores in China's and rural public schools (solid line) and private migrant schools (dotted line).

**Table 2.** Summary statistics of the standardised maths scores

| Maths scores by sample | Rural public schools | Private migrant schools | Δ Scores | Significance of difference (*p*-value) |
|---|---|---|---|---|
| Standardised maths scores of students | | | | |
| Overall sample | 0.81 | −0.30 | −1.11 | 0.000*** |
| Geographically matched subsample | 0.81 | −0.34 | −1.15 | 0.000*** |
| Standardised maths scores of peers | | | | |
| Overall sample | 0.86 | −0.36 | −1.22 | 0.000*** |
| Geographically matched subsample | 0.86 | −0.43 | −1.29 | 0.000*** |

*Note*: *** represent a significance level of 1%;# = Reference group.

comparison when examining the scores of students from the overall sample or the geographically matched subsample, using either of the two datasets. On average, using the overall sample, the students in rural public students scored 0.81 SDs on the standardised maths test. In contrast, students in private migrant schools scored an average of −0.30 SDs. The difference in the two sets of scores (rural public vs. migrant students) was 1.11 SDs. The difference, using the geographically matched subsample, was equally large (1.15 SDs). In the education literature, these performance gaps can be considered quite large (Koedel & Betts, 2007).

### 4.3. Peer effects

The descriptive statistics show that peers in private migrant schools performed significantly worse than did peers in rural public schools (Table 2). This is true for both the overall sample (using Dataset 1) and the geographically matched sample (using Dataset 2). Peers in rural public schools scored an average of 0.86 SDs on the standardised maths test. In contrast, students in private migrant schools scored an average of −0.36 SDs. The difference in the two sets of scores (rural vs. migrant students), using Dataset 1, was 1.22 SDs. At the same time, the difference in test scores between migrant and rural students, using Dataset 2, was 1.29 SDs. Based on the results in Table 2, we also can conclude that, on average, each student in a rural public school had a peer with relatively better educational performance, whereas the student in a private migrant school had a peer with relatively worse performance. The characteristics of the school, teacher, family/individuals are presented in Supplementary Materials (Tables A1 and A2).

### 4.4. Multivariate results

In this section, we report the results of the multivariate analysis in the school fixed effects estimation strategies to meet the remaining objectives of the study. To do so, first, we used an OLS regression approach for Equations (2) to evaluate school quality, peer effect, and interacted effects on individual academic performance, using the overall sample (Table 3). Second, controlling for a subset of

**Table 3.** Ordinary least squares regressions for the overall sample

| | Students' standardised maths scores | | | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| School (Migrant schools = 1) | −0.857*** | −0.405** | −0.287 | −0.305* |
| | (15.57) | (2.24) | (1.62) | (1.74) |
| Peer effects | | | 0.158*** | 0.293*** |
| | | | (9.74) | (10.14) |
| School*Peer | | | | −0.251*** |
| | | | | (7.60) |
| Control variables | | | | |
| School effects | No | Yes | Yes | Yes |
| Homeroom teacher effects | No | Yes | Yes | Yes |
| Students and family characteristics | No | Yes | Yes | Yes |
| School fixed effects | Yes | Yes | Yes | Yes |
| Constant | 1.090*** | 1.179** | 0.989** | 1.113** |
| | (10.91) | (2.37) | (2.02) | (2.30) |
| $F$-value | 38.93*** | 55.32*** | 57.47*** | 57.33*** |
| Adjusted $R^2$ | 0.392 | 0.522 | 0.535 | 0.543 |
| Obs. | 4668 | 4668 | 4668 | 4668 |

*Notes*: *, **, and *** represent a significance level of 10%, 5%, and 1%, respectively; $t$-values, calculated using robust standard errors, are reported in parentheses.

**Table 4.** Ordinary least squares regressions for the geographically matched subsamples

| | Students' standardised maths scores | | | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| School (Migrant schools = 1) | −0.849*** | 0.140 | 0.219 | 0.145 |
| | (9.19) | (0.42) | (0.68) | (0.47) |
| Peer effects | | | 0.243*** | 0.293*** |
| | | | (10.23) | (10.30) |
| School*Peer | | | | −0.239*** |
| | | | | (5.40) |
| Control variables | | | | |
| Schools and classes | No | Yes | Yes | Yes |
| Homeroom teacher | No | Yes | Yes | Yes |
| Students and family characteristics | No | Yes | Yes | Yes |
| School fixed effects | Yes | Yes | Yes | Yes |
| Constant | 1.310 | 1.221 | 1.019 | 1.282 |
| | (12.28) | (1.61) | (1.38) | (1.72) |
| Adjusted $R^2$ | 0.266 | 0.351 | 0.420 | 0.426 |
| Obs. | 2268 | 2268 | 2268 | 2268 |

*Note*: *** represent a significance level of 1%; *t*-values, calculated using robust standard errors, are reported in parentheses.

**Table 5.** First-stage regressions of the 2SLS regressions for the overall sample

| | Peers' standardised maths scores | | School*Peers' standardised maths scores |
|---|---|---|---|
| Variable | (1) | (2) | (3) |
| School (Migrant schools = 1) | −0.898*** | −0.936*** | −0.109*** |
| | (5.20) | (5.34) | (8.79) |
| $IV_1$: Education of peer's mother | 0.420*** | 0.426*** | −0.011*** |
| | (17.12) | (8.49) | (2.97) |
| $IV_2$: Education of peer's father | 0.453*** | 0.408*** | 0.007** |
| | (18.41) | (7.83) | (2.00) |
| $IV_3$: School*Education of peer's mother | | −0.012 | 0.426*** |
| | | (0.21) | (16.72) |
| $IV_4$: School*Education of peer's father | | 0.070 | 0.472*** |
| | | (1.21) | (19.09) |
| Control variables | | | |
| Schools and classes | Yes | Yes | Yes |
| Homeroom teacher | Yes | Yes | Yes |
| Student and family characteristics | Yes | Yes | Yes |
| School fixed effects | Yes | Yes | Yes |
| Constant | 0.264 | 0.280 | 0.751 |
| | (0.58) | (0.61) | (2.29) |
| *F*-value | 592.89*** | 343.76*** | 302.48 *** |
| Adjusted $R^2$ | 0.556 | 0.556 | 0.477 |
| Obs. | 4668 | 4668 | 4668 |
| Durbin-W-Hausman Chi-square test | 0.010 [1.00] | 8.570 [1.00] | |
| Weak identification test | | | |
| Cragg-Donald Wald *F*-statistic | 606.87 | 169.18 | |
| Stock-Yogo bias critical values (10%) | 19.93 | 16.87 | |
| Over-identification test | | | |
| Hansen *J*-statistic | 0.006 [0.94] | 1.619 [0.45] | |

*Note*: ** and *** represent a significance level of 5% and 1%, respectively; *t*-values, calculated using robust standard errors, are reported in parentheses; *p*-values are reported in brackets.

**Table 6.** Two-stage least squares (2SLS) regressions for the overall sample

| | Students' standardised maths scores | | | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| School (Migrant schools = 1) | −0.857*** | −0.405*** | −0.285* | −0.263 |
| | (15.75) | (2.27) | (1.62) | (1.51) |
| Peer effects | | | 0.161*** | 0.443*** |
| | | | (5.41) | (5.95) |
| School*Peer | | | | −0.401*** |
| | | | | (5.08) |
| Characteristics of schools and classes | | | | |
| Operating life | | 0.012** | 0.011** | 0.003 |
| | | (2.34) | (2.61) | (0.62) |
| Share of teacher with advanced certificates | | 1.104*** | 0.982*** | 1.071*** |
| | | (3.13) | (2.82) | (3.14) |
| Male-female ratio | | 0.560*** | 0.521*** | 0.270* |
| | | (4.14) | (3.90) | (1.88) |
| Class size | | −0.014*** | −0.011*** | −0.009** |
| | | (3.05) | (2.58) | (2.08) |
| Characteristics of homeroom teachers | | | | |
| Teacher ranking | | −0.001 | 0.041 | 0.017 |
| | | (0.01) | (0.16) | (0.06) |
| Gender | | −0.169 | −0.179 | −0.127 |
| | | (0.96) | (1.02) | (0.72) |
| Age | | −0.014** | −0.015** | −0.009 |
| | | (1.79) | (1.98) | (1.19) |
| Maths teacher | | 0.588*** | 0.523*** | 0.353** |
| | | (4.29) | (3.83) | (2.50) |
| Characteristics of students and their families | | | | |
| Age | | −0.118*** | −0.109*** | −0.106*** |
| | | (9.73) | (9.12) | (8.80) |
| Gender | | 0.053** | 0.037* | 0.033 |
| | | (2.47) | (1.77) | (1.54) |
| Single child | | −0.034 | −0.033 | −0.038 |
| | | (1.12) | (1.09) | (1.26) |
| Family size | | −0.011 | −0.011 | −0.016* |
| | | (1.14) | (1.18) | (1.68) |
| Education of father | | 0.486*** | 0.478*** | 0.479*** |
| | | (19.62) | (19.65) | (19.92) |
| Education of mother | | 0.322*** | 0.315*** | 0.304*** |
| | | (12.64) | (12.50) | (12.09) |
| School fixed effects | Yes | Yes | Yes | Yes |
| Constant | 1.090*** | 1.179** | 0.985** | 1.103** |
| | (11.04) | (2.40) | (2.04) | (2.30) |
| Wald Chi-square | 4101.24*** | 6640.59*** | 6812.69*** | 6709.09*** |
| Adjusted $R^2$ | 0.378 | 0.509 | 0.523 | 0.526 |
| Obs. | 4668 | 4668 | 4668 | 4668 |

*Note*:*, **, and *** represent a significance level of 10%, 5%, and 1%, respectively; *t*-values, calculated using robust standard errors, are reported in parentheses.

unobservables, we use the geographically matched subsample to further test the effects of school quality, peer effects, and its interaction effect (Table 4). Third, the two-stage least squares (2SLS) method with IVs was used to quantitatively identify the effects of peers and school quality on the students' performance (Tables 5 and 6). As in the case of the OLS results, we also repeat the 2SLS estimates, using the geographically matched subsample (Table 7).[2]

**Table 7.** Robustness check of 2SLS regressions for the geographically matched subsamples

| | Students' standardised maths scores | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| School (Migrant schools = 1) | −0.849*** | 0.140 | 0.240 | 0.134 |
| | (9.41) | (0.43) | (0.77) | (0.45) |
| Peer effects | | | 0.307*** | 0.449*** |
| | | | (5.93) | (6.12) |
| School*Peer | | | | −0.404*** |
| | | | | (4.37) |
| Control variables | | | | |
| Schools and classes | No | Yes | Yes | Yes |
| Homeroom teacher | No | Yes | Yes | Yes |
| Student and family characteristics | No | Yes | Yes | Yes |
| School fixed effects | Yes | Yes | Yes | Yes |
| Constant | 1.310*** | 1.221* | 0.966 | 1.363* |
| | (12.57) | (1.65) | (1.34) | (1.86) |
| Adjusted $R^2$ | 0.355 | 0.432 | 0.462 | 0.459 |
| Obs. | 2268 | 2268 | 2268 | 2268 |

*Note*: * and *** represent a significance level of 10% and 1%, respectively; *t*-values, calculated using robust standard errors, are reported in parentheses.

*4.4.1. OLS estimations of school quality effect and peer effects.* Table 3 presents the OLS estimated results for the Equation (2), using the overall sample. In Column 1, we include only the migrant school dummy variable to measure the overall raw gap between the maths scores of rural and migrant students. By design, this gap (0.857) is smaller than the raw gap that is shown in table of descriptive statistics when controlling for the school fixed effects (Table 2).

In Column 2, we presents the results of measuring the conditional gap by adding a set of variables that measure school/teacher and family/individual characteristics to the regression specification in Column (1), which includes only the migrant school dummy variable. Conditional on these other factors, there is still a gap (0.405) between the scores of migrant and rural students. Therefore, as found in other studies, the observed quality differences between the school facilities/other characteristics and, especially, teachers and individuals/families are able to explain part of the gap in the scores between rural and migrant students (Wang et al., 2017).

To show how much of this conditional gap is explained by peer effects, per se, we estimate and present the results of Equation (2). In this specification, we add the variable that measures the effect of one's peer on each student to the regression specification in Equation (2).[3] The findings (Column 3) show that the size of the conditional gap (now also conditional on peer effects in addition to the other control variables) shrinks to 0.287 SDs. The coefficient of the peer effects variable is positive (0.158) and statistically significant. Other variables held constant, the presence of peers in schools (for the average student, including both rural and migrant students) is shown to be associated with higher performance.

Finally, in Table 3, Column 4, we add an interactive term between the dummy variable for migrant school and the peer effects variable. The results clearly show that, in addition to the migrant school dummy variable as still negative and significant (−0.305) and the peer variable as still positive and significant (0.293), the interaction term is negative and significant (−0.251). These results suggest that there is a significantly different association between peers in rural schools and those students in migrant schools. Specifically, the coefficient on the rural school peer effects variable (Column 4) is positive and significant (0.293) and larger than the average effect (0.158) in Column 3. The correlation between peers also has a positive effect on students in migrant schools, but the magnitude is smaller (0.293–0.251 = 0.042). The sum of the coefficients of the school and the interaction effects of the peers, which represents the peer effects for the migrant students, is also significantly different from zero. These results, then, show the way that peers in rural schools and the quality of schools – students in rural schools have higher test scores than students in migrant schools – interact positively to enhance student performance.

We also use the geographically matched subsample to check the robustness of the OLS results, which are presented in Table 4. When using the geographically matched subsample (one that perhaps has relatively fewer unobservables), the results are almost completely the same. Migrant-rural and conditional gaps are nearly the same as those estimated in Table 3. As seen in Column 3, the coefficient of the average (for migrants and rural students) peer effect variable (0.243), although slightly larger in magnitude than the coefficient of the average peer effect in the larger sample (0.158), when testing the difference between 0.243 and 0.158, does not yield a difference that is statistically significant. The signs and magnitudes of the coefficients, when allowing for heterogeneous peer effects across school types, also are the same when using the overall sample (Dataset 1 in Table 3) and the geographically matched subsample (Dataset 2 in Table 4). In short, the results are robust to the nature of the sample.

*4.4.2. Instrumental variable estimations of the school quality effect and peer effects.* To test the validity of our OLS results and to assess whether we should use our IV strategy, we first conduct a Durbin-W-Hausman test to determine whether there is an endogeneity problem that could influence the estimation of the relationship between peer effects and maths test scores. In fact, our results show that there is an endogeneity issue and that the OLS results could be biased in terms of evaluating peer effects and the interacted term of school quality on the student's school outcome. Thus, an IV methodology is used in the remainder of the study to identify the causality of peer effects and its interacted term on the student's academic performance.

To control for the endogeneity of a peer's academic performance in explaining the student's outcome, we use the educational levels of the peer's parents and their interacted term with the school dummy as IVs. Table 5 presents the estimation results of the first stage of the IV analysis for the overall sample. With the peer effects variable on the left side and the education level of the parents of the peer of each student one the right side (and holding the other school/teacher and family/individual characteristics constant), the estimated coefficients indicate that the educational levels of the peer's father and mother have a positive and significant effect on the peer's academic performance (Columns 1 and 2). We also document that there is no significant relationship between the educational attainment of the peer's parents and the standardised maths scores of the peer's peer (that is, the students in the sample). These findings lend support to the conclusion that the exclusion restriction of our chosen IVs is valid (Supplementary Materials Table A3).

We also can use a number of other statistical tests beyond the Durbin-W-Hausman test to examine the validity of the IVs that we use in this study. As shown in Table 5, when using either the Cragg-Donald Wald test or the Stock-Yogo test to check for the presence of a weak identification of the IVs, the results reject the null hypothesis that there is weak identification at the 1 per cent level of significance. We also use the Hansen $J$ statistic to test whether overidentification occurs when we use our study's IVs (Table 5). The results also show that the IVs used in this study do not have overidentification issues. Hence, consistent with our multiple tests of logic, we conclude that using the education levels of the parents of a student's peers to identify the impact of a peer on a student's own outcomes should be valid.

In using our IV strategy to estimate Equations (3) and (4), which are the IV counterparts that were presented in Table 3 (for Dataset 1), we find that the results are nearly the same.[4] As seen in Table 6, Column 3, the estimated relationship, using the IV approach between the peer effects variable and standardised maths score variable for the average of both migrants and rural students, is 0.161 (significant at the 1% level). As with the case of the measurement of the conditional gap, the IV estimated coefficient that measures the effect of peers on maths scores is only slightly different than the OLS estimated coefficient in Table 3. Likewise, the interaction effects are similar. The data

**Table 8.** Decomposition analysis for decomposing student maths scores between rural public and private migrant schools by conditional migrant school gap, peer effects, school quality, and teacher/student/family characteristics

| Variable | Explained gap | Explanatory power (%) |
|---|---|---|
| Difference in the standardised maths scores (private/public) | −1.11 | |
| Difference in the standardised maths scores by unobserved school quality (private/public) | −0.26 | 23.42% |
| Difference in the peer effects (private/public) | −0.14 | 12.61% |
| Peer effects in private migrant schools | 0.40 | |
| Peer effects in rural public schools | 0.54 | |
| Characteristics of school, class, and homeroom teacher | −0.40 | 36.04% |
| Characteristics of students and their families | 0.05 | −4.50% |
| Explained difference | | 67.57% |
| Unexplained difference | | 32.43% |

*Note*: decomposing gaps are calculated from the coefficients for the 2SLS regression results for the overall sample from Table 6, Column 4.

support the hypothesis that there is a complementary relationship between peer effects and the quality of the school in a causal way. We include the coefficient of the variable that measures the characteristics of school and class, homeroom teacher, and the student and his or her family (Table 6), as they are used in the decomposition analysis.

As seen in Table 7, we repeat the 2SLS analysis, using the smaller (in terms of observations) geographically matched sample.[5] In general, the results are similar to those from the 2SLS estimated models that use the overall sample (Table 6). The first-stage regression results of the 2SLS analysis are presented in Supplementary Materials Table A4. When a peer effect is added (Column 3), the average peer effect is still statistically significant with the magnitude of 0.307. When the interaction term of school dummy and peer are included (Column 4), the results show that, on average, the positive peer effect is much larger in the rural public school than that in the migrant school. This again suggests that students' outcomes are higher when students have positive interactions with higher-performing peers.

### *4.5. Decomposing the source of education gap*

We also decompose student maths scores by the quality of schools, peer effects, and other observed school and teacher characteristics as well as student and family characteristics (Table 8). Based on the overall sample, the educational gap between the students in private migrant school and rural public school is −1.11 SDs. In total, the decomposition analysis is able to explain nearly 70 per cent (67.57 = 100–32.43) of the overall raw academic performance gap. The analysis of the conditional gap, explained by the school type dummy, explains 45.05 per cent of the educational gap. Our inclusion of the peer effects in the analysis demonstrates the importance of peer effects in accounting for the educational gap in different types of schools. Indeed, the gap due to the different peer effects (−0.14 = 0.40–0.54) accounts for approximately 12.61 per cent of the difference in the standardised maths scores. This is about 19 per cent (12.61%/67.57%) of the explainable gap between migrant and rural schools. The difference in the observable school and class and homeroom teacher characteristics explain 36.04 per cent of the gap. The characteristics of the student and their family could explain −4.50 per cent of the gap between the private migrant schools and rural public schools.

## 5. Discussion and conclusion

Peer effects and school quality play important roles in determining the academic performance of students. Nevertheless, knowledge of the interaction effects of peers and the quality of the schools is limited. Using unique survey data from over 4,500 students from both private migrant and rural public schools in China, this study not only examines the impact of peers and school quality on student academic performance but also tests for interaction effects.

The results show a stable positive relationship between the standardised maths scores of students and their peers. The estimation results, using a 2SLS approach to identify causality, confirm that students whose peers have higher maths scores tend to perform better on standardised maths scales compared with those whose peers have poorer maths scores. In addition, because our analysis shows that the average quality of rural public schools is greater than that of private migrant schools, the average standard maths scores of students in the public schools are even higher than those of students in private migrant schools. Hence, the observable gaps in student academic performance can be explained by the differences in the quality of their schools, including teachers and school facilities, and the outcomes of the peers of students.

The results of the analysis that examines the interaction of peers and school quality indicates that the peer effect seen in rural public schools is larger than that of private migrant schools. This finding reveals that school quality has complementary effects with peers in terms of student academic performance. Thus, both the improvement of school quality and the formation of small groups within classes may help to reduce the educational gaps between students in private migrant and rural public schools.

There are limitations to this study. In the analysis, we use school fixed effects to correct any bias in the estimated coefficient on the migrant school variable. This approach controls for all non-time-varying unobservables and should allay some of the concerns about bias. We do recognise, however, that there may be unobservable time-varying effects that could potentially bias the coefficient. To the extent that these are present, there may be some bias in our estimated coefficients. The further research should pay special attention to this issue.

## Notes

1. To the best of our acknowledge, peer effects have been examined at both grade or class level (Burke & Sass, 2011; Ding & Lehrer, 2007; Kang, 2007; Lai, 2008; Li et al., 2014) and individual or group level within a class or dormitory (Brady, Insler, & Rahman, 2017; Lu & Anderson, 2015; Sacerdote, 2001, 2011; Song, Loewenstein, & Shi, 2018; Winston & Zimmerman, 2003).
2. As an additional robustness check, we used the one-to-one peer subsample to eliminate the effect of overweighting the importance of individual students who were identified as being a peer to more than one student (Tables A5–A7).
3. Alternatively, we use another definition of peers in the estimation of peer effects as a robustness check. We define peer effects as the average scores of all of the other classmates in a class (Carman & Zhang, 2012; Lai, 2008). The results, which are consistent with those in Tables 3 and 4, are available upon request.
4. In the case of Tables 5 and 6, we also have conducted a robustness check by including county fixed effects. Although we do not report the results due to space limitations, there are not any material differences in the results when compared to the results in Tables 5 and 6. The results when using county fixed effects are available from the authors upon request.
5. The robustness check of the results by using one-to-one peer subsample is presented in Supplementary Materials Appendix B.

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No potential conflict of interest was reported by the author(s).

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