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Classmates and friends matter! Peer effects on cognitive ability formation☆

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ABSTRACT

In this paper, we investigate the impact of peer effects on cognitive ability formation at two different levels – class peers and close friends simultaneously. We use random class assignments in the China Education Panel Survey (CEPS) to deal with ability sorting and self-selection into classroom when estimating class peer effects. To identify close friend peer effects, we include initial human capital to control for time-invariant unobservables, as stable friendship implies that unobserved preference based on which students make friends is likely to stay unchanged, especially within the one-year frame of the data. We find significant positive peer effects on students' cognitive ability formation at both levels. Peer effects are heterogeneous across student ability. Peer effects work through two channels – peer conformity and peer complementarity. We find both channels generate positive peer effects and jointly determine the size of overall estimated peer effects.

1. Introduction

A famous proverb says, "One takes on the color of one's company." In the real world, one's behaviors are indeed affected to some extent by their interactions or relationships with others around them. Peer effects represent how an individual's decision-making or performance is directly influenced by their peers' outcomes or characteristics. These effects are commonly observed in schools (Frölich & Michaelowa, 2011; Gong, Lu, & Song, 2019; Harris, 2011; Hoxby, 2000; Lépine & Estevan, 2021) and workplaces (Card, Mas, Moretti, & Saez, 2012; Falk & Ichino, 2006; Guryan, Kroft, & Notowidigdo, 2009; Mas & Moretti, 2009; Rosaz, Slonim, & Villeval, 2016; Welteke & Wrohlich, 2019). Researchers have been studying what peer effects are, how to measure them, how impactful they are, and how they work (Arnott & Rowse, 1987; Epple & Romano, 1998; Epple & Romano, 2008). Understanding peer effects can provide useful policy implications for improving education outcomes. It is a meaningful and informative way to help improve schooling quality from a new perspective and accelerate human capital accumulation at the early stages of life.

In this paper, we study the context of middle school education in China, to test how peer effects impact students' cognitive ability formation at two different levels, globally via class peers and locally via close friends. There exists related literature looking into peer effects from more than one group at the same time, for example, from one's study group and roommates (Jain & Kapoor, 2015) or from

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short-term peers and long-term peers (Patacchini, Rainone, & Zenou, 2017). Our peer clusters are different not only in size, but also in the intimacy of peer relationships. Peer effects are not always positive, they can be disruptive (Card & Giuliano, 2013; Carrell, Hoekstra, & Kuka, 2018; Lazear, 2001). Following this set of literature, we consider both positive and disruptive close friend peer effects.

It is challenging to measure peer effects through students' peer interactions, because these interactive behaviors are usually unobservable. In our study, we focus on estimating endogenous effects defined in Manski (1993) and adopt the linear-in-means model to measure the class peer effects. Some researchers employ network properties to measure peer effects (Bramoullé, Djebbari, & Fortin, 2009; Bramoullé, Kranton, & D'amours, 2014; Calvó-Armengol, Patacchini, & Zenou, 2009; Goldsmith-Pinkham & Imbens, 2013). Because we do not have detailed information on network links or pairwise interactions, we use behavioral variables to measure close friend peer effects.

Moreover, there is a broad consensus that it is difficult to identify peer effects because of endogeneity issues. Some researchers separate peer effects from many confounding factors by controlling for student and school-by-grade fixed effects (Hanushek, Kain, Markman, & Rivkin, 2003; Lin, 2010), while others explore random peer group assignments as a treatment for self-selection (Carrell, Sacerdote, & West, 2013; Feld & Zölitz, 2017; Jain & Kapoor, 2015; Lu & Anderson, 2015; Sacerdote, 2001; Zimmerman, 2003). In our identification strategy, we first control for family characteristics, school fixed effects, and teacher experience, to separate peer effects from other effects also influencing students' educational outcomes. In the meantime, we take advantage of the random class assignment information from the data to deal with ability sorting and self-selection into classroom. Furthermore, we include initial human capital to control for time-invariant unobservables that are correlated with close friend selection. To address the reflection problem in the contemporaneous peer effects, we use lagged variables to measure peer effects. In addition to introducing controls and random assignments, some researchers employ IV approaches to identify peer effects. Angrist (2014) points out 2SLS estimates of peer effects could suffer from the weak IV problem. We propose potentially useable IVs to address remaining concerns about the self-selection into the close friend network. However, good IVs are hard to find within the data, and we encounter weak IV problems like the literature. Nevertheless, our inclusion of initial human capital can help identify the close friend peer effects by controlling for the time-invariant unobservables based on which students make friends. As one's close friends likely change little within the one-year frame of the data, the initial human capital correlating with the close friend peer effects through unobserved heterogeneity can partial out a significant amount of the omitted variables from the error term. Therefore, we focus on the random assignment identification strategy with initial human capital controlled for. As a robustness check, we propose potential IVs and panel data fixed effect models to mitigate the remaining concerns on endogeneity.

Peer effects are found to be asymmetric between the short and long runs (Patacchini et al., 2017), as well as over the ability distribution (Jain & Kapoor, 2015). To contribute to this set of literature, we employ quantile regression techniques to investigate the peer effect heterogeneity by ability quantiles. We find asymmetric peer effects by quantiles of student ability distribution.

Furthermore, we explore the mechanisms that determine overall peer effects. We identify two working channels and designate them as peer conformity and peer complementarity. In this paper, we refer to peer conformity as the situation where competition among peers drives one to exert more effort and peer complementarity as the knowledge spillover that lowers learning cost. Blume, Brock, Durlauf, and Jayaraman (2015) also discuss social conformity and peer complementarity as two channels that generate identical peer effects. Our work differs from Blume et al. (2015) in two major ways. First, we incorporate peer complementarity and peer conformity in one single model, while Blume et al. (2015) model them separately. Second, we respectively test the channels in empirical models, while Blume et al. (2015) cannot distinguish them. Inspired by Feld and Zölitz (2017) and Mehta, Stinebrickner, and Stinebrickner (2019), we use peer relationship variables to proxy the complementarity channel and student effort variables to proxy the conformity channel. We find that both generate positive peer effects. Overall, the magnitude of estimated peer effects is jointly determined by the two channels. The results also suggest that peer effect heterogeneity by quantiles is driven by the fact that higher competition generates a higher level of social conformity for highest-achieving students, whereas knowledge spillover creates larger complementarity effects for lower-achieving students. This finding implies from a social standpoint that it is optimal to maximize both conformity and complementarity effects to generate the largest peer effects. To do so, schools and parents can encourage students to learn from their classmates and close friends, and to form a healthy competitive relationship with them.

Our contributions to the literature are threefold. Firstly, we develop a framework on human capital formation, in which peer effects play roles at two different levels, globally via class peers and locally via close friends. Secondly, we use one single model to incorporate the two channels–peer conformity and peer complementarity that jointly determine peer effects. Thirdly, we empirically test the two channels and use them to explain asymmetric peer effects by ability quantiles.

The rest of the paper is organized as follows. Section 2 sets up the theoretical framework. Section 3 describes the data and introduces the identification strategy. Section 4 analyzes and discusses the baseline results. Section 5 explores mechanisms through which peer effects drive cognitive ability formation and heterogeneous peer effects by quantiles. Section 6 further investigates endogeneity issues by applying IV approaches and fixed effect models in addition to the random class assignments and the control of initial human capital. Section 7 concludes.

2. A theoretical framework

Suppose there are n students ($n \geq 2$) in a network (e.g., classmates or close friends). We assume that the student i chooses the level of human capital h_{it} to obtain at time t after observing peer human capital in the previous period $t-1$, to maximize his or her utility:

$$\max_{h_{it}} u(h_{it})\pi\left(e\left(\overline{h}_{-i(t-1)}\right), h_{it}, h_{i0}, X_{it}, u_{it}\right) - c\left(e\left(\overline{h}_{-i(t-1)}\right), h_{it}, h_{i0}, \overline{h}_{-i(t-1)}\right), \tag{1}$$

where $\overline{h}_{-i(t-1)} \equiv \frac{1}{n-1}\sum_{j\neq i}^{n} h_{j(t-1)}$ denotes peer human capital. $u(\cdot)$ is a utility function increasing in h_{it}, student i's target human capital to obtain. $\pi(\cdot)$ is the probability of achieving the target human capital h_{it}. The probability $\pi(\cdot)$ is decreasing in the target h_{it} and increasing in the initial human capital h_{i0} and the effort exertion $e(\cdot)$. The likelihood $\pi(\cdot)$ to achieve h_{it} also depends on the observable characteristics X_{it} (e.g., personal characteristics, family background, teacher quality, and school effects) and unobservable u_{it} of i. The expected utility $u(\cdot)\pi(\cdot)$ is a concave function. The concave functional property implies $\frac{\partial u(\cdot)\pi(\cdot)}{\partial h_{it}} > 0$ and $\frac{\partial^2 u(\cdot)\pi(\cdot)}{\partial {h_{it}}^2} < 0$. The effort input is an increasing function of peer human capital $\overline{h}_{-i(t-1)}$, that is $\frac{\partial e(\cdot)}{\partial \overline{h}_{-i(t-1)}} > 0$. The intuition is that conformity or peer competition incentivizes the focal student i to exert more effort toward human capital investment after observing peer achievement. $c(\cdot)$ is a human capital investment convex cost function with properties $\frac{\partial c(\cdot)}{\partial e(\cdot)} > 0$, $\frac{\partial c(\cdot)}{\partial h_{it}} > 0$, $\frac{\partial c(\cdot)}{\partial h_{i0}} < 0$, and $\frac{\partial c(\cdot)}{\partial \overline{h}_{-i(t-1)}} < 0$. Effort exertion $e(\cdot)$ is costly. As the target human capital h_{it} is higher, the associated cost increases. More capable students with higher h_{i0} are more efficient in human capital investment. Students with higher-ability peers $\overline{h}_{-i(t-1)}$ benefit from knowledge spillover through peer interactions and thus enjoy lower learning cost.

For simplicity, we assume $u(h_{it}) = \alpha_1 h_{it}$, where $\alpha_1 > 0$; $e\left(\overline{h}_{-i(t-1)}\right) = e_1\overline{h}_{-i(t-1)}$, where $e_1 > 0$; $\pi\left(e\left(\overline{h}_{-i(t-1)}\right), h_{it}, h_{i0}, X_{it}, u_{it}\right) = \pi_1 e_1\overline{h}_{-i(t-1)} - \pi_2 h_{it} + \pi_3 h_{i0} + X_{it}b + u_{it}$,[1] where π_1, π_2, $\pi_3 > 0$; $c\left(e\left(\overline{h}_{-i(t-1)}\right), h_{it}, h_{i0}, \overline{h}_{-i(t-1)}\right) = c_1 e_1\overline{h}_{-i(t-1)} + c_2 h_{it}^2 - c_3\overline{h}_{-i(t-1)}h_{it} - c_4 h_{i0} - c_5\overline{h}_{-i(t-1)}$, where c_1, c_2, c_3, c_4, $c_5 > 0$. Then, the maximization problem (1) becomes

$$\max_{h_{it}} \left(\pi_1 e_1\overline{h}_{-i(t-1)} - \pi_2 h_{it} + \pi_3 h_{i0} + X_{it}b + u_{it}\right)\alpha_1 h_{it} - \left(c_1 e_1\overline{h}_{-i(t-1)} + c_2 h_{it}^2 - c_3\overline{h}_{-i(t-1)}h_{it} - c_4 h_{i0} - c_5\overline{h}_{-i(t-1)}\right). \tag{2}$$

We solve the utility maximization problem and get the first order condition:

$$\alpha_1\left(\pi_1 e_1\overline{h}_{-i(t-1)} + \pi_3 h_{i0} + X_{it}b + u_{it}\right) + c_3\overline{h}_{-i(t-1)} - 2(\alpha_1\pi_2 + c_2)h_{it} = 0. \tag{3}$$

Therefore, the human capital choice of i is

$$h_{it} = \frac{\alpha_1\pi_1 e_1 + c_3}{2(\alpha_1\pi_2 + c_2)}\overline{h}_{-i(t-1)} + \frac{\alpha_1\pi_3}{2(\alpha_1\pi_2 + c_2)}h_{i0} + X_{it}\frac{\alpha_1 b}{2(\alpha_1\pi_2 + c_2)} + \frac{\alpha_1}{2(\alpha_1\pi_2 + c_2)}u_{it}. \tag{4}$$

We denote $\theta = \frac{\partial h_{it}}{\partial \overline{h}_{-i(t-1)}} = \frac{\alpha_1\pi_1 e_1 + c_3}{2(\alpha_1\pi_2 + c_2)}$. Given α_1, π_2, $c_2 > 0$, the denominator $2(\alpha_1\pi_2 + c_2)$ is positive. In the numerator, $e_1 = \frac{\partial e\left(\overline{h}_{-i(t-1)}\right)}{\partial \overline{h}_{-i(t-1)}} > 0$, that is, the effort input is an increasing function of peer human capital $\overline{h}_{-i(t-1)}$. The intuition is that conformity or peer competition incentivizes the focal student i to exert more effort toward human capital investment after observing peer achievement. Together with $\alpha_1 > 0$ and $\pi_1 > 0$, the social conformity or peer competition suggests that the first term $\alpha_1\pi_1 e_1 > 0$. We refer to this channel as peer conformity. The second term $c_3 = -\frac{\partial^2 c(\cdot)}{\partial h_{it}\partial \overline{h}_{-i(t-1)}} > 0$ implies when peer human capital $\overline{h}_{-i(t-1)}$ is increasing, the marginal cost associated with gaining an additional unit of h_{it} is decreasing through knowledge spillover by interacting with more capable peers. We refer to this channel as peer complementarity. Putting all together, the magnitude of peer effects is jointly determined by the two channels–peer conformity and peer complementarity. Both channels generate positive peer effects, leading to $\theta = \frac{\partial h_{it}}{\partial \overline{h}_{-i(t-1)}} > 0$. In addition, we let $\gamma = \frac{\alpha_1\pi_3}{2(\alpha_1\pi_2 + c_2)}$, $\beta = \frac{\alpha_1 b}{2(\alpha_1\pi_2 + c_2)}$, and $\mu_{it} = \frac{\alpha_1}{2(\alpha_1\pi_2 + c_2)}u_{it}$ to rewrite i's human capital choice (4) as

$$h_{it} = \theta\overline{h}_{-i(t-1)} + \gamma h_{i0} + X_{it}\beta + \mu_{it}. \tag{5}$$

Our model suggests that individual human capital choice depends on previous peer human capital, own initial human capital, and individual characteristics. Additionally, it generates an important insight that peer effects work through two channels–peer conformity that results in the student effort exertion and peer complementarity that lowers learning costs. We go beyond Blume et al. (2015) by incorporating two channels in one single model, and we test them empirically in Section 5.

3. Data and empirical models

3.1. Data description and peer effect measures

For the empirical study, we use the latest data from the China Education Panel Survey (CEPS), a project designed to be nationally representative to support research on the effects of family, school, community, and social structure on educational outcomes at the individual level. CEPS consists of several questionnaires on individual students, parents or guardians, class head teachers, subject teachers, and school principals (administrators). The survey randomly samples 112 middle schools from 28 counties in China. Currently, there are two waves of data available on the CEPS website[2]: the 2013–2014 baseline data and the 2014–2015 follow-up

[1] We assume the linear probability function for simplicity and focus on the interior solutions falling in [0,1].

[2] CEPS Details: https://ceps.ruc.edu.cn/

data.

In CEPS, some schools randomly assign students into classes at the beginning of Grade 7. We follow the three conditions in Gong, Lu, and Song (2018) and add one more to restrict our sample: (i) in the 2013–2014 baseline survey, the school principal reported that they randomly or evenly assign students into different classes at the beginning of Grade 7; (ii) in the 2013–2014 baseline survey, the same principal reported no rearrangement of classes for Grade 7 students since the semester during which the baseline survey took place; (iii) in the 2013–2014 baseline survey, no head teachers in the same school that taught Grade 7 reported that students in this grade were assigned into classes by test scores; (iv) in the 2014–2015 follow-up survey, the school principal reported no rearrangement of classes for Grade 8 students (Grade 7 in 2013–2014) since the semester during which the follow-up survey took place. These four conditions can ensure the students in our sample were randomly assigned into classes when they entered Grade 7 and remained in the same class in Grade 8. The random sample contains 3953 students randomly assigned to 97 classes at 50 schools. To remove the sorting and self-selection of students into classrooms, we explore the random class assignments in the data and restrict our estimation of class peer effects using the random sample.

The measurement we use for cognitive ability is the score of a uniform cognitive test carried out by the CEPS team. Based on individual cognitive scores, we measure class peer effects by the traditional linear-in-means model, that is, the class average cognitive score excluding student i's cognitive score. In the survey, students were first asked to write down five names of their best friends truthfully and then asked how many of their best friends were doing well in academic performance ("Good Performance") and how many were having disruptive behaviors like "Skipping Class".[3] Since we do not have the student ID to track the listed friends in the same class within the data, we are not able to calculate a linear-in-means cognitive score for the close friend peers. Therefore, we use these two friend-related behavioral questions to measure the close friend peer effects. Table 1 defines and summarizes the measures of peer effects and cognitive ability. Table 2 defines and summarizes other variables such as student characteristics, teacher quality, instrumental variables, and working channels.

Although we do not observe the student ID of the listed friends, we do observe whether they are in the same class, in another class at the same school, or outside the school where the surveyed student attends. Across the surveyed individuals in the data, on average around 65% of listed friends are in the same class with them, that is about 3 out of 5 listed friends. Roughly 35% of the total surveyed students listed all their 5 best friends as in the same class as them. As one can imagine, there is certainly an overlap between the class network and the close friend network, but the size is very small. On average 3 listed friends are in the same class, while the mean class size is about 45. This evidence suggests the composition of the close friend network can be very different from that of the class network.

Figure 1 illustrates the relationship between two levels of peer networks, the close friend peer network contains part of the class peer network if the listed friends are in the same class, part of the school peer network if the listed friends are at the same school but not in the same class, and part of the peer network outside school if the listed friends are not at the same school. Therefore, the close friend peer effects account for part of class peer effects, as well as additional network effects outside class and school. Close friend peer effects have a small overlap with class peer effects but capture more network aspects than class peer effects. Also, friendship is more intimate, and the interactions are more frequent in the close friend network than in the class network.

3.2. Identification strategies

In our estimation, we focus on the identification of the endogenous peer effects as characterized by Manski (1993). To define the scope of peers, we borrow the concepts of local and global linkages from Benabou (1996) and let $\overline{h}_{-i(t-1)} = \left(H_{-i(t-1)}, L_{-i(t-1)}\right)$, where $H_{-i(t-1)}$ denotes classmate human capital and $L_{-i(t-1)}$ denotes close friend human capital. Our model differs from Benabou (1996) in that we define a local linkage as one's close friends (Card & Giuliano, 2013) and a global linkage as their classmates, while Benabou (1996) refers to a community as the local linkage and the whole labor market as the global linkage. Based on the theoretical framework and the discussions on class peers and close friends, we assume the linear value-added model to capture class and close friend peer effects on student i's cognitive ability:

$$y_{itcs} = \theta_H H_{-i(t-1)cs} + \theta_L L_{-i(t-1)cs} + \beta_y y_{i0cs} + x_i\beta_x + f_i\beta_f + t_c\beta_t + d_s\gamma + \epsilon_{itcs}, \tag{6}$$

where y_{itcs} is individual i's cognitive ability test score at time t in class c of school s. We include the test score in the initial period y_{i0cs} as a proxy for initial human capital. To deal with the reflection problem pointed out by Manski (1993), we use lagged peer effect variables at time $t-1$ to avoid simultaneity between the student cognitive ability and the contemporaneous peer effects. The class peer human capital $H_{-i(t-1)cs}$ is measured by the class average score without counting i. The close friend human capital $L_{-i(t-1)cs}$ is measured by friend-related variables discussed above. x_i includes individual i's personal characteristics, such as gender, age, and health status. f_i partials out the nature and nurture effects by parental years of education and financial status respectively. t_c stands for teacher quality proxied by teachers' years of teaching experience. d_s controls for school effects by including school dummies.

Based on the baseline model, we further consider the endogeneity concerns resulting from two aspects: (i) ability sorting and self-selection into classes; (ii) self-selection based on unobserved characteristics into close friend networks. To address the selection into

[3] The answer scale of both questions is as following: 1 - None of them doing well in academic performance (skipping classes), 2 - One or two of them doing well in academic performance (skipping classes), 3 - Most of them doing well in academic performance (skipping classes). For the convenience of interpretation, we convert the value into the number of peers: 0 - None of them, 1.5 - One or two of them, 4 - Most of them. Since the conversion is monotonic, we have the sign of coefficients of interest to be consistent with the original variables.

Table 1
Summary statistics of peer measurements and cognitive ability.

Variable	Definition	Obs	Mean	Std	Min	Max
Peer Effects						
Class Peers						
Class Peer Cognitive Score 2014	Self-excluded Class Mean	3953	0.143	0.516	−1.369	1.406
Close Friend Peers						
Close Friend Good Performance 2014	Number of Friends	3884	2.608	1.381	0	4
Close Friend Skipping Class 2014	Number of Friends	3871	0.106	0.509	0	4
Cognitive Ability						
Cognitive Score 2015	Follow-up Cognitive Score	3923	0.387	0.831	−3.137	2.063

Table 2
Variable definition and summary statistics.

Variable	Definition	Obs	Mean	Std	Min	Max
Student Characteristics						
Grade6 Class Top25%	1-Yes, 0-No	3506	0.433	0.496	0	1
Gender (Male)	1-Male, 0-Female	3953	0.513	0.500	0	1
Age	Number of Years	3953	14.462	0.648	13	17
Good Health 2015	1-Very good/good, 0-o.w.	3917	0.653	0.476	0	1
Number of Siblings 2015	Num. of Full/half siblings	3915	0.549	0.757	0	12
Parent Highest Year of Edu	Years of Highest Degree	3946	11.607	3.184	0	19
Subsistence Allowance 2015	1-Receipt, 0-No	3748	0.081	0.273	0	1
Teacher Quality						
Head Teacher Experience 2015	Years of Teaching	3949	15.834	7.516	3	35
Chn Teacher Experience 2015	Years of Teaching	3821	15.219	8.087	2	40
Math Teacher Experience 2015	Years of Teaching	3853	16.250	8.511	1	35
Eng Teacher Experience 2015	Years of Teaching	3913	16.701	8.341	3	34
Instrumental Variables						
Commuting Minutes	Home to School Commuting	3818	22.941	29.413	0	650
School Transfers	Trans. Num. Primary Sch.	3943	0.371	0.811	0	9
Class Peer Family to Care 2015	1-Yes, 0-No, Class Mean	3786	0.102	0.056	0	0.367
Channel Variables						
Peer Conformity						
HW Hours 2015	HW Hours on Weekdays	3944	2.147	0.944	0	4
Study Attitudes 2015	1-Not Serious at all ..0.5-Very Serious	3877	3.348	0.963	1	5
Peer Complementarity						
Classmates Nice To Me 2015	1-Strongly Disagree ..0.4-Strongly Agree	3937	3.322	0.759	1	4
Close to School Peers 2015	1-Strongly Disagree ..0.4-Strongly Agree	3930	3.029	0.883	1	4

classes, we restrict our estimations to the sample students who are randomly assigned into classrooms. Conditional on fixed effects of schools at which the randomization takes place, regressions on the random sample reduce the class peer effect estimation bias resulting from endogenous class formation. To validate the randomization of class assignments, we perform balance tests in Table 3. CEPS team randomly surveys two classes per school. If a school randomly assigns students into classes, students in the surveyed two classes should have no significant difference in their predetermined characteristics. We generate a class indicator variable equal to 1 if a student belongs to one surveyed class at a school and 0 if he or she belongs to the other surveyed class at that school. In Table 3, each row represents a separate regression of corresponding predetermined characteristic on the class indicator variable conditional on school fixed effects with robust standard errors. All coefficients are statistically insignificant, suggesting that two surveyed classes, conditional on the school fixed effects, do not differ in predetermined student characteristics. The balance test results indicate that our class randomization setting is valid.

In the estimations, y_{i0cs} controls for not only the initial ability in a value-added model, but also the time-invariant unobserved characteristics that matter in cognitive ability formation. Therefore, the inclusion of y_{i0cs} can help mitigate the endogeneity concerns caused by possible self-selection on unobserved characteristics into the close friend network. The small cross-time variation of close

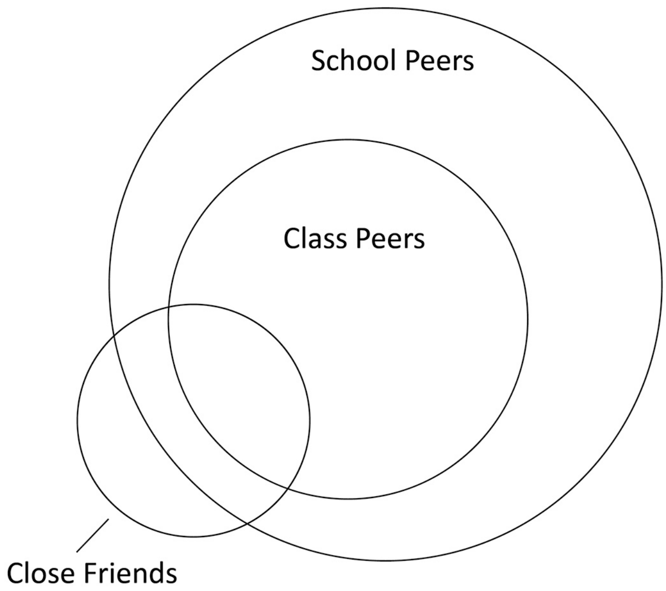

Fig. 1. Relationship between Class peers and close friends.

Table 3
Balance test for predetermined student characteristics.

	(1)	(2)	(3)
	Coefficient	S.E.	Observations
Grade6 Class Top25%	−0.008	(0.017)	3506
Gender (Male)	−0.002	(0.016)	3953
Age	0.021	(0.019)	3953
Good Health 2015	−0.005	(0.015)	3917
Number of Siblings 2015	0.015	(0.022)	3915
Parental Highest Year of Education	−0.078	(0.083)	3946
Subsistence Allowance Receipt 2015	0.006	(0.008)	3748

Two classes per school are included in the survey data. A class indicator variable is equal to 0 if a student belongs to the 1st class at a school and 1 if he or she belongs to the 2nd class at that school. Each row represents a separate regression of corresponding predetermined characteristic on the class indicator variable conditional on school fixed effects. Robust standard errors are reported in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

friend peer measures indicates that the composition of one's close friends is relatively stable over time. Thus, the unobserved preference for making friends is likely to vary little within the one year between the baseline survey and the follow-up one. Therefore, the inclusion of initial human capital can do a good job in helping identify the close friend peer effects by taking care of the potential correlation between close friend peer effect regressors and the time-invariant unobservables that can influence cognitive formation. One might have doubts that the initial human capital could not control for all the unobserved heterogeneity that matters for friendship formation, especially those varying over time. Hence, we apply IV approaches and fixed effects models as robustness checks on these concerns in Section 6.

4. Baseline estimates of class and close friend peer effects

In this section, we run OLS with robust standard errors to estimate both class and close friend peer effects. We use the random class assignments to address the endogeneity from the sorting and selection into classes and include the initial human capital proxied by the Grade 6 class ranking indicator to control for the unobserved factors based on which students make friends.

Theoretically speaking, the random assignments of students into classes remove the selection issue due to ability sorting by schools. On the one hand, the random class assignments assign students into classes; on the other hand, it can be viewed as assigning teachers into classes as well. Therefore, the random class assignments can remove the endogenous part of teacher quality effects. Provided that the teacher's effects are usually positive, the random class assignments should generally lower the class peer effects and the close friend peer effects if listed friends are in the same class. From the comparison between the results in Table 4 and Table A1, we can see that the class peer effects about 0.126–0.139 estimated in the random sample are smaller than 0.338–0.357 estimated in the full sample, which is consistent with our theoretical prediction. The close friend peer effects have mixed changes between the full sample results and the

Table 4
Random sample OLS estimates of class and close friend peer effects.

	(1)	(2)	(3)
	Cog. Score 2015	Cog. Score 2015	Cog. Score 2015
Class Peer Cognitive Score 2014	0.139**		0.126*
	(0.049)		(0.049)
Close Friend Good Performance 2014		0.023*	0.023*
		(0.009)	(0.009)
Close Friend Skipping Class 2014		−0.126***	−0.125***
		(0.027)	(0.027)
Grade6 Class Top25%	0.441***	0.434***	0.433***
	(0.023)	(0.024)	(0.024)
Gender (Male)	−0.029	−0.010	−0.010
	(0.023)	(0.024)	(0.023)
Age	−0.129***	−0.125***	−0.126***
	(0.020)	(0.020)	(0.020)
Good Health 2015	0.021	0.010	0.012
	(0.025)	(0.025)	(0.025)
Number of Siblings 2015	0.002	0.001	0.002
	(0.019)	(0.019)	(0.019)
Parental Highest Year of Education	0.016***	0.017***	0.017***
	(0.005)	(0.005)	(0.005)
Subsistence Allowance Receipt 2015	−0.082	−0.068	−0.071
	(0.048)	(0.048)	(0.048)
Head Teacher Experience 2015	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)
Math Teacher Experience 2015	−0.003	−0.005	−0.004
	(0.003)	(0.003)	(0.003)
Chinese Teacher Experience 2015	0.002	0.003	0.002
	(0.002)	(0.002)	(0.002)
English Teacher Experience 2015	−0.003	−0.000	−0.002
	(0.003)	(0.003)	(0.003)
Constant	2.063***	1.996***	1.950***
	(0.315)	(0.316)	(0.317)
School Fixed Effects	Yes	Yes	Yes
Observations	3107	3052	3052
R2	0.401	0.409	0.411

Robust standard errors in parentheses
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

random sample results. For the close friends, the estimates of good-performing friend peer effects are slightly reduced from 0.026 to 0.027 in the full sample to 0.023 in the random sample but remain statistically significant. When looking at the disruptive friends, the random sample estimates of the peer effects caused by friends who skipped class are marginally more negative than the full sample ones.

As Manski (1993) points out, the identification of peer effects is subject to the reflection problem, that is, the peers can affect the focal individual while the individual can affect their peers. To address this classic reflection problem, we use lagged peer measures. As we can see in Table 4, Column (1) only includes class peer effects. The average cognitive score of class peers has a significantly positive effect on an individual's score. Column (2) only considers close friend peer effects and controls for teaching experience in addition to school fixed effects.[4] Having more good-performing close friends generates positive effects on an individual's cognitive ability. Making disruptive friends disturbs student cognitive ability formation. Column (3) is our preferred specification that incorporates class and close friend peer effects simultaneously into the model conditional on school fixed effects.[5] The results show that a 1-point increase in class peer average scores leads to a 0.126-point increase in an individual score. Having one additional friend doing well in academic performance results in an increase in one's cognitive score by around 0.023 points. However, having one additional friend with bad behaviors such as skipping class reduces an individual's own cognitive score by about 0.125 points. A disruptive friend seems to have a

[4] One may be concerned that teacher experience regressors cannot fully capture unobserved class characteristics. In order to address these concerns, we replace teacher experience with class fixed effects that capture teacher quality and other unobserved class heterogeneity. Similar estimates of close friend peer effects in Column (2) and the regressions with class fixed effects suggest that teacher quality, conditional on school fixed effects, accounts for most class inputs that are correlated with peer effects in student cognitive ability accumulation.

[5] If we included the class fixed effects instead of school fixed effects, we would find the class peer effects to be negative. This does not mean that the true class peer effects are negative. Rather, this is because the class peer effect measurement has a very small variation by linear-in-means construction. The little-varying self-excluded class averages are highly collinear with class fixed effects, resulting in noisy negative estimates. Therefore, we do not control for class fixed effects when we use the linear-in-means model to measure the class peer effects. In fact, the randomization of class assignments takes place at the school level, and the inclusion of school fixed effects can ensure the conditional randomization of class peers.

larger influence than a friend who performs well.

The magnitude of estimated class peer effects is close to that in the literature using random assignments. Carman and Zhang (2012) estimate that under the classroom assignments of comparable student quality, a 1 standard deviation increase in average Math score among peers results in a 0.37 standard deviation increase in one's Math score, and a 1 standard deviation increase in peer average Chinese score is associated with a 0.42 standard deviation increase in an individual score. The main reason for the difference between our estimate and that in Carman and Zhang (2012) could be that our estimate is measured by points and theirs is by standard deviation. Also, we estimate peer effects on cognitive ability while they estimate peer effects on exam scores. The peer effect estimate using random assignment information of students to classrooms in Tennessee elementary schools through Project STAR in Whitmore (2005) is about 0.6. The main reason for the difference between our estimate and Whitmore (2005)'s could be that we further partial out the positive teacher effects from peer effects, whereas Whitmore (2005) does not control for teacher effects. The other reasons could be attributed to the data being obtained from different grades and education system differences. We use the data from Grade 7 to 8 in Chinese middle schools, while Whitmore (2005) uses the data from kindergarten to Grade 3 in the U.S. The findings of close friend peer effects are consistent with the literature exploring friendship peer effects (Bramoullé et al., 2009; Patacchini et al., 2017).

In terms of gender difference, the results indicate that female students tend to have higher cognitive development than their male peers, but the difference is statistically insignificant. In addition, the OLS results suggest that older students tend to perform worse than their counterparts. The significantly negative coefficient of age is somewhat unexpected. The negative age effect is counter-intuitive because one would expect that cognitive ability increases with age. We can interpret this finding as older students staying in the same grade as their younger peers, such as kids who are repeating a grade, might have less-developed cognitive skills compared to their counterparts of the same age. Therefore, the significantly negative effect of age on cognitive scores is capturing this effect rather than suggesting the counter-intuitive implication that cognitive ability decreases with age.

The human capital literature shows that cognitive ability is inherited from parents and affected by family nutrition. The positive though insignificant coefficients on health status are in line with the literature showing the impact of family nutrition and health status on cognitive ability. One would expect that individuals would perform better if they were the only child, because they would not have to share the family's educational recourses with siblings. However, the estimated coefficients on the number of siblings are statistically insignificant. The main reason causing this insignificance could be the potential high correlation between different regressors, especially initial human capital accumulated during primary school, which may be highly correlated with many time-invariant control variables. The significantly positive coefficients on parental highest year of education are consistent with theoretical predictions that more educated parents are more willing to invest in their children's education and their children have higher cognitive ability than their counterparts. One would expect that a wealthier family would have more resources to invest in their children's education. Thus, the students from families with better financial conditions would perform better. The dummy of low-income subsistence allowance receipt indicates poor family financial conditions. The negative coefficients on poor family indicators are as expected.

The traditional teacher quality literature suggests that students taught by more experienced teachers tend to perform better. However, we do not see significant positive teacher quality effects in Table 4.[6] The reasons could be (i) the random assignments of students into classes can be viewed as the random assignments of teachers into classes as well, therefore, on average the effects from teacher experience become insignificant conditional on controlling for school fixed effects; (ii) the linear-in-means class peer measures have small variations around a constant which could be collinear with the teacher experience that is constant for every student in the same class.

5. Mechanisms and quantile heterogeneity of peer effects

In this section, we take a step forward to investigate the mechanisms of peer effects. Peer effects work through peer conformity and peer complementarity in our theoretical model. We now employ specific measurements to test the two working channels. One channel is peer conformity where competition rises among students via peer interactions. When students observe how well their peers perform and how hard their peers work, it starts to push students and incentivize them to put more effort into studying. We measure the effort exertion by "Homework Hours on Weekdays" and "Study Attitudes".[7] They are respectively defined by the question "From Monday to Friday, how much time on average every day did you spend on doing homework assigned by teachers?" from the student survey and "What do you think of the general attitude of this child towards schoolwork?" from the parent survey. Column (1) and (2) of Table 5 show the conformity channel results. The estimates in Column (1) suggest that good peers, regardless of class peers or close friends, can significantly increase student effort exertion on homework. We see no effect from disruptive peers on homework effort. Column (2) indicates that close friends have a more significant impact on study attitudes than class peers. The empirical results are consistent with our theoretical prediction that better peers motivate a student to work harder, leading to a higher level of cognitive ability. The

[6] Alternatively, we use professional job title, credential status, tenure status, whether a teacher graduated from a normal college, and whether a teacher won an excellent teacher award, respectively, to proxy teacher quality. For those specifications, we find similar estimates for peer effects at both levels and the estimates of corresponding teacher quality are mixed and insignificant. These results are available upon request.

[7] Our measurement of channels may not be perfect. In our framework, the conformity channel levels up the competition intensity that generates positive peer effects. Our ideal proxies for the conformity channel would be variables that directly measure competition, for example, the focal student's attitudes towards the situation when their peers are better than them. Unfortunately, we don't have such direct questions in the survey to use. Due to this data limitation, we use measures of effort exertion to proxy competition. These alternative measures may capture a lot of noise other than competition.

Table 5
Mechanisms of peer effects.

	Peer Conformity		Peer Complementarity	
	(1)	(2)	(3)	(4)
	HW Hours 2015	Study Attitude 2015	Classmates Nice To Me 2015	Close To School Peers 2015
Class Peer Cognitive Score 2014	0.264***	0.026	−0.019	−0.045
	(0.075)	(0.069)	(0.057)	(0.066)
Close Friend Good Performance 2014	0.035**	0.074***	0.033**	0.069***
	(0.012)	(0.012)	(0.010)	(0.012)
Close Friend Skipping Class 2014	−0.026	−0.093*	−0.063	−0.061
	(0.036)	(0.038)	(0.034)	(0.035)
Grade6 Class Top25%	−0.001	0.503***	0.098***	0.099**
	(0.033)	(0.034)	(0.027)	(0.031)
Gender (Male)	−0.119***	−0.301***	−0.075**	−0.038
	(0.032)	(0.033)	(0.026)	(0.030)
Age	−0.005	−0.029	−0.028	−0.028
	(0.027)	(0.027)	(0.022)	(0.026)
Good Health 2015	−0.075*	0.083*	0.210***	0.326***
	(0.035)	(0.035)	(0.029)	(0.034)
Number of Siblings 2015	−0.032	−0.092***	−0.004	−0.042
	(0.027)	(0.027)	(0.022)	(0.027)
Parental Highest Year of Education	0.010	0.004	0.006	0.004
	(0.006)	(0.007)	(0.005)	(0.006)
Subsistence Allowance Receipt 2015	0.028	−0.004	−0.015	0.018
	(0.065)	(0.061)	(0.051)	(0.058)
Head Teacher Experience 2015	0.005	−0.004	−0.006	−0.008*
	(0.004)	(0.004)	(0.003)	(0.004)
Math Teacher Experience 2015	−0.006	−0.002	−0.006*	−0.007*
	(0.003)	(0.004)	(0.003)	(0.003)
Chinese Teacher Experience 2015	0.006*	0.004	0.006*	0.005
	(0.003)	(0.003)	(0.003)	(0.003)
English Teacher Experience 2015	0.001	0.010*	−0.003	0.003
	(0.005)	(0.005)	(0.004)	(0.004)
Constant	2.045***	3.547***	3.729***	3.169***
	(0.438)	(0.432)	(0.343)	(0.409)
School Fixed Effects	Yes	Yes	Yes	Yes
Observations	3070	3054	3069	3061
R2	0.182	0.187	0.107	0.167

Robust standard errors in parentheses
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

literature also finds effort channels in peer effects (Gong et al., 2018; Mehta et al., 2019).

The other channel is peer complementarity where knowledge spillover occurs among students throughout peer interactions. On the one hand, if knowledge transfers from the high-ability students to the low-ability students, it reduces the learning cost of the low-ability students who would have to spend much more time attaining the same knowledge on their own. On the other hand, a group of high-ability students can exchange their private information with each other and make all pieces of the puzzle fall into place, also reducing the learning cost of the high-ability. Thus, peer interactions can generate positive effects on cognitive development through the channels of reducing learning cost or improving learning efficiency. Our measurements for peer complementarity are "Classmates Nice to Me" and "Close to School Peers".[8] The two measures are defined by the student survey questions (i) "How much do you agree with the statement that most of my classmates are nice to me?" and (ii) "I feel close to people in this school." Column (3) and (4) of Table 5 show the results of the complementarity channel. Only good-performing close friends matter in student own evaluation of peer relationships while class peers and disruptive close friends do not. Our assumption is that good peer relationships can facilitate complementary learning activities and helping each other with schoolwork, generating positive peer effects on student cognitive formation. As good-performing close friends are usually the ones we turn to for help, it makes sense that they play a significant role in the complementarity channel.

One would speculate that these two channels have asymmetric effects on students depending on their ability, resulting in heterogeneous peer effects. We run quantile regressions in Table 6 to estimate heterogeneous peer effects at different quantiles of cognitive ability distribution. Figure 2 illustrates the corresponding peer effect estimates conditional on the different cognitive ability quantiles. As we can see, the class peer effects are the largest on the bottom 25% quartile and the smallest on the above-average

[8] The imperfect measurement issue applies to the variables representing the complementarity channel. The ideal proxy for the complementarity channel would be the direct measure of peer interactions like discussions on schoolwork. Due to the data limitation, however, we have to go for the current measures of peer relationships that can facilitate these complementary learning activities.

Table 6
Peer effect heterogeneity by ability quantiles.

	(1) 0–25%	(2) 25–50%	(3) 50–75%	(4) 75–100%
	Cog. Score 2015	Cog. Score 2015	Cog. Score 2015	Cog. Score 2015
Class Peer Cognitive Score 2014	0.249**	0.104*	0.090*	0.123*
	(0.094)	(0.049)	(0.045)	(0.051)
Close Friend Good Performance 2014	0.030**	0.035***	0.024**	0.012
	(0.009)	(0.009)	(0.007)	(0.009)
Close Friend Skipping Class 2014	−0.110**	−0.143***	−0.098*	−0.094***
	(0.041)	(0.031)	(0.040)	(0.019)
Grade6 Class Top25%	0.520***	0.453***	0.395***	0.300***
	(0.024)	(0.024)	(0.020)	(0.023)
Gender (Male)	−0.096***	−0.039	0.029	0.081***
	(0.029)	(0.025)	(0.020)	(0.023)
Age	−0.168***	−0.125***	−0.097***	−0.081***
	(0.022)	(0.022)	(0.017)	(0.018)
Good Health 2015	0.054	0.004	−0.015	−0.034
	(0.040)	(0.027)	(0.020)	(0.024)
Number of Siblings 2015	0.009	−0.011	−0.008	−0.017
	(0.022)	(0.024)	(0.015)	(0.020)
Parental Highest Year of Education	0.015**	0.013**	0.016***	0.019***
	(0.006)	(0.005)	(0.004)	(0.004)
Subsistence Allowance Receipt 2015	−0.049	−0.026	−0.040	−0.078*
	(0.052)	(0.058)	(0.042)	(0.031)
Head Teacher Experience 2015	−0.001	−0.002	0.002	0.008*
	(0.006)	(0.003)	(0.003)	(0.003)
Math Teacher Experience 2015	−0.001	−0.003	−0.002	0.001
	(0.004)	(0.004)	(0.003)	(0.003)
Chinese Teacher Experience 2015	0.002	0.002	0.002	−0.000
	(0.003)	(0.002)	(0.002)	(0.003)
English Teacher Experience 2015	−0.002	−0.006	−0.001	−0.004
	(0.006)	(0.005)	(0.004)	(0.004)
Constant	1.773***	1.948***	1.870***	1.784***
	(0.485)	(0.340)	(0.276)	(0.269)
School Fixed Effects	Yes	Yes	Yes	Yes
Observations	3052	3052	3052	3052

estimation results are obtained by quantile regressions that condition the dependent variable, cognitive score, on the specified quantile of its distribution.
Robust standard errors in parentheses
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

50–75% quartile. We can explain this pattern using two channels. The low-ability students would enjoy the knowledge spillover mainly generated by the high-ability. Therefore, the low-ability students are more likely than the high-ability to benefit more from peer complementarity effects. It suggests that the peer effects stemming from peer complementarity are decreasing as the ability moves from the left tail to the right tail of the distribution. That is in line with the descending trend from the bottom 25% quartile to the 50–75% quartile. The merit-based education system in China makes students conform to the higher end of the ability distribution, leading to larger peer conformity effects among the highest-ability students. Hence, the top 25% quartile sees a jump in the class peer effects as the conformity channel reinforces the complementarity channel. At the local level, the good-performing close friend peer effects are roughly decreasing as cognitive ability moves to the right tail. For the top 25% quartile, it even becomes insignificantly different from zero. This trend indicates that the driver is the complementarity channel in good close friend peer effects. Also, the conformity effect from good-performing close friends seems to be absent in the top 25% quartile. The estimated disruptive close friend peer effects are larger for the below-average quartiles of ability distribution. The dominant channel in disruptive peer effects is peer conformity, such that the low-ability students are more likely to mimic disruptive behaviors of their kind.

6. Further investigation on endogeneity

In Section 4, we use the random class assignments to address the sorting and selection into classes, and we use the inclusion of the initial human capital to mitigate the self-selection into close friend networks based on the unobserved characteristics, especially time-invariant ones. One might still be concerned that the initial human capital cannot fully control for the unobserved characteristics that matter for friendship formation, for example, those that vary over time. Hence, we further apply IV approaches to address these

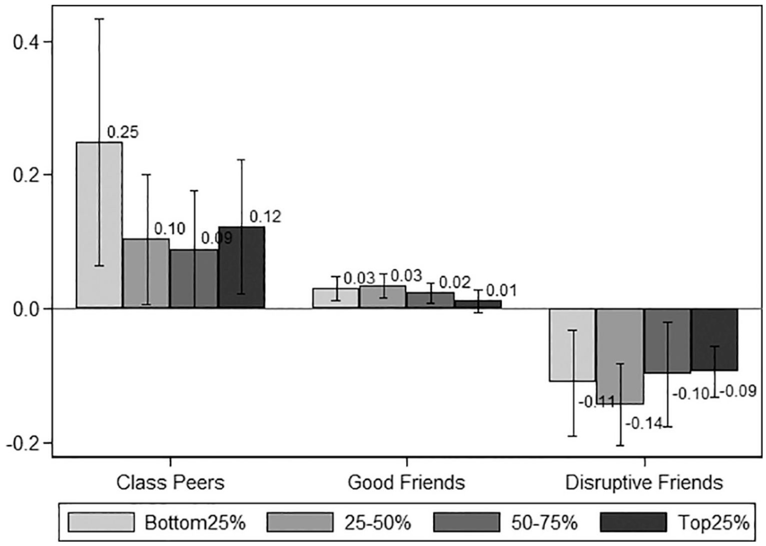

Fig. 2. Peer effect heterogeneity by ability quantiles.
The estimates are obtained by quantile regressions in Table 6. Confidence intervals are at 95% level.

concerns.

We employ two IVs: (i) "School Transfers" defined as the number of school transfers during the primary school Grade 1 to 6 at the individual level of surveyed students; (ii) "Commuting Minutes" defined as the individual commuting time in minutes from home to school. Our argument for IVs is that school transfers and school-home distance do not affect students' cognitive ability directly since they are relatively exogenous conditional on initial human capital,[9] which satisfies the exclusion restriction. The corresponding relevance condition is that they are more likely to influence the children cognitive ability indirectly through the close friend network interactions because their close friend network can be changed by school transfers or affected by having limited time for interactions with peers.

We now use our preferred baseline model specification in Column (3) of Table 4 to address the remaining concerns about the endogeneity at the close friend level. Table 7 uses IVs to instrument the close friend peer effects only. The estimates of class peer effects and close friend peer effects become insignificant when close friend peer effects are instrumented. The reason could be that the IVs in use suffer from weak instrument problems as indicated by the first stage results in Table A2. The inflation of our 2SLS estimates of close friend peer effects compared to the OLS ones in absolute terms is consistent with the literature. Angrist and Lang (2004) find that some 2SLS estimates are implausibly larger than the corresponding OLS estimates. Ammermueller and Pischke (2009) find the IV estimates on peer effects are at least 30% and up to >100% higher than the OLS ones. The weak IV problems outweigh the potential gain from further extenuating the residual endogeneity given that initial human capital is being controlled for. Our IV results here only serve as a robustness check.

Our empirical analysis so far is conducted in the cross-sectional framework. As we have two time periods, we could have constructed the panel data with a minimum of two periods. The main reasons for not using panel data approaches are (i) the primary school rank is only available in the baseline survey such that it does not allow us to control for initial cognitive ability in the panel data; (ii) our close friend peer measures have limited variation over the one-year gap; (iii) many cognitive determinants are time-invariant. Column (1) in Table 8 shows the fixed effects estimates for peer effects using the sample of random class assignments in the panel data setting. The class peer effects have much larger estimates than those in the cross section. The reason could be that panel data approaches incorporate both the within-individual value-added variations from 2014 to 2015 and the between-individual variations. Furthermore, there is no lagged cognitive ability controlled for in the panel data framework due to the data limitation. In addition, we see that after canceling out the unobserved time-invariant fixed effects, the close friend peer effect estimates are not statistically significant from zero, which is driven by the limited variation in the close friend composition within just one year. As one might be still worried that fixed effects models cannot handle the unobserved time-varying heterogeneity that affects close friend peer effects, so we employ the FEIV model to address this concern. For the full rank condition, we must have at least two time-varying IVs for the two measures of close friend peer effects. However, the related questions for two IVs "School Transfers" and "Commuting Minutes" are asked in only one survey wave, thus they have no variation across time to satisfy the full rank condition for FEIV models. Therefore, we use another IV "Class Peer Family to Care", defined as the self-excluded class average of the indicator whether a student has family

[9] The number of school transfers and the school-home distance can be correlated with student academic performance as Chinese parents often transfer their kids or move close to better schools for better education quality. Our control of initial human capital can partial out the IV-correlated part, based on which the transferring and moving decisions are made, from the error term.

Table 7
Random sample 2SLS estimates of class and close friend peer effects.

	(1)	(2)	(3)
	Cog. Score 2015	Cog. Score 2015	Cog. Score 2015
Class Peer Cognitive Score 2014	0.121*	0.102	0.107
	(0.052)	(0.071)	(0.069)
Close Friend Good Performance 2014	0.152		0.154
	(0.264)		(0.231)
Close Friend Skipping Class 2014		−0.892	−0.258
		(1.434)	(1.638)
Grade6 Class Top25%	0.389***	0.425***	0.380***
	(0.097)	(0.033)	(0.087)
Gender (Male)	0.008	0.065	0.038
	(0.071)	(0.144)	(0.165)
Age	−0.120***	−0.096	−0.108
	(0.025)	(0.054)	(0.060)
Good Health 2015	−0.007	0.006	−0.008
	(0.049)	(0.030)	(0.043)
Number of Siblings 2015	0.008	0.017	0.012
	(0.028)	(0.039)	(0.042)
Parental Highest Year of Education	0.011	0.017**	0.012
	(0.010)	(0.006)	(0.009)
Subsistence Allowance Receipt 2015	−0.059	−0.057	−0.056
	(0.060)	(0.068)	(0.078)
Head Teacher Experience 2015	0.002	0.004	0.004
	(0.003)	(0.004)	(0.003)
Math Teacher Experience 2015	−0.004	−0.005	−0.004
	(0.003)	(0.004)	(0.004)
Chinese Teacher Experience 2015	0.002	−0.000	0.000
	(0.003)	(0.004)	(0.005)
English Teacher Experience 2015	−0.003	0.003	−0.001
	(0.004)	(0.009)	(0.009)
Constant	1.582	1.570	1.375
	(0.887)	(0.813)	(1.165)
School Fixed Effects	Yes	Yes	Yes
Observations	3061	2986	2976
R2	0.362	0.184	0.354

In Column (1), Close Friend Good Performance 2014 is instrumented by School Transfers; in Column (2), Close Friend Skipping Class 2014 is instrumented by Commuting Minutes; in Column (3), two close friend measures are instrumented by School Transfers and Commuting Minutes.
Robust standard errors in parentheses
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

members who need long-term care because of health or mobility problems, to instrument for one close friend peer measure at a time in Column (2) and (3), but the respective estimates are still not significantly different from zero. Besides FEIV, we could have done REIV as well, but the data with only two periods leave us no room to find additional IVs within the panel system.

In sum, our investigation of the endogeneity issues shows that the potential gain from our further treatment for residual endogeneity caused by unobserved time-varying heterogeneity based on which students make friends is outweighed by weak IV problems and insufficient variation of close friends within just one year of our data. The insignificant FE estimates potentially resulting from the little time-varying close friend measures could be comforting, such that our inclusion of initial human capital can do well in controlling for time-invariant unobservables to deal with endogeneity in close friend peer effects.

7. Conclusions

In this paper, we find evidence for the existence of strong peer effects in China's middle schools using CEPS data. The students learning with more intelligent peers build higher ability themselves as well. Good surroundings are very important for students' ability formation. Making friends with those who behave badly hurts students' cognitive development. In addition, the estimated effects from family, i.e., parental education and nutrition, and teacher quality are as expected and consistent with the literature. Peer effects work through the channels of peer conformity (more effort exertion) and peer complementarity (lower learning cost). Both channels generate positive effects on the overall peer effect estimates and jointly determine the size of peer effects on human capital formation. The peer effect estimates are asymmetric across the cognitive ability distribution, and this heterogeneity can be explained by the two working channels. The potential policy implications for schools and parents are to encourage students to learn from their classmates and close friends, and to form a healthy competitive relationship with them.

Table 8
Panel Data fixed effects and FEIV estimates of peer effects.

	(1)	(2)	(3)
	Cog. Score	Cog. Score	Cog. Score
Class Peer Cognitive Score	0.932***	1.068***	1.013***
	(0.033)	(0.302)	(0.220)
Close Friend Good Performance	−0.007	0.507	
	(0.008)	(1.099)	
Close Friend Skipping Class	−0.005		−1.597
	(0.018)		(3.822)
Number of Siblings	0.047	0.025	−0.024
	(0.027)	(0.061)	(0.173)
Good Health	−0.041	−0.087	−0.143
	(0.026)	(0.122)	(0.268)
Subsistence Allowance Receipt	−0.030	−0.030	0.021
	(0.046)	(0.074)	(0.153)
Head Teacher Experience	0.001	0.003	0.025
	(0.003)	(0.006)	(0.057)
Constant	0.050	−1.290	−0.031
	(0.055)	(2.855)	(0.157)
Observations	7201	7146	7131

In Column (1), the FE estimates are reported; in Column (2)–(3), the FEIV estimates are reported. In Column (2), well-behaved close friend peer measure is instrumented by the time-demeaned Class Peer Family to Care; in Column (3), the misbehaved close friend peer measure is instrumented by the time-demeaned Class Peer Family to Care. The other two IVs - Commuting Minutes and School Transfers are available in only one survey wave, thus they are not time-varying to be used as IVs in FEIV for the full rank condition.
Robust standard errors in parentheses
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Data availability

Data are available at https://ceps.ruc.edu.cn/.

Appendix

Table A1: Full Sample OLS Estimates of Class and Close Friend Peer Effects.

	(1)	(2)	(3)
	Cog. Score 2015	Cog. Score 2015	Cog. Score 2015
Class Peer Cognitive Score 2014	0.357***		0.338***
	(0.038)		(0.037)
Close Friend Good Performance 2014		0.027***	0.026***
		(0.006)	(0.006)
Close Friend Skipping Class 2014		−0.118***	−0.115***
		(0.020)	(0.020)
Individual Characteristics	Yes	Yes	Yes
Teacher Experience	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes
Observations	6543	6433	6433
R2	0.379	0.377	0.385

Robust standard errors in parentheses
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A2: First stage for 2SLS estimates of class peer and close friend peer effects.

	(1)	(2)	(3)	(4)
	Close Friend	Close Friend	Close Friend	Close Friend
	Good Performance	Skipping Class	Good Performance	Skipping Class
	2014	2014	2014	2014
Number of School Transfers	−0.063		−0.068*	−0.004
	(0.033)		(0.034)	(0.014)
Commuting Minutes		0.000	−0.001	0.000
		(0.001)	(0.001)	(0.001)

(continued on next page)

(*continued*)

	(1)	(2)	(3)	(4)
	Close Friend	Close Friend	Close Friend	Close Friend
	Good Performance	Skipping Class	Good Performance	Skipping Class
	2014	2014	2014	2014
Class Peer Effects 2014	Yes	Yes	Yes	Yes
Individual Characteristics	Yes	Yes	Yes	Yes
Teacher Experience	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes
Observations	3082	3006	3008	3002
R2	0.110	0.054	0.110	0.055

Robust standard errors in parentheses
$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

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