

The Peer Effect of Persistence on Student Achievement*

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Abstract

Little is known about the impact of peer personality on human capital formation. This paper studies the peer effect of persistence, a personality trait that reflects perseverance when facing challenges and setbacks, on student achievement. Exploiting student-classroom random assignments in middle schools in China, I find having more persistent peers improves in student achievement. The effects are prominent in students with high and medium baseline persistence. I find three mechanisms: (i) students' own persistence and self-disciplined behaviors increase; (ii) teachers become more responsible/patient and spend more time on teaching preparation; and (iii) endogenous friendship networks consisting of more academically successful peers and fewer disruptive peers develop, particularly among students who share with similar levels of persistence.

Keywords: Peer effect; Personality trait; Human capital; Friendship formation

JEL Classification: I21, I24, J24

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1 Introduction

The key role of non-cognitive skills in affecting education and labor market outcomes has been well documented. The predictive power of non-cognitive skills, such as personality traits, rivals that of cognitive abilities in improving life-cycle outcomes (Borghans et al., 2008; Almlund et al., 2011; Kautz et al., 2014). However, while many studies have investigated the direct effects of non-cognitive skills on human capital formation, evidence related to the peer effect remains scarce. Uncovering the impact of peers' personality traits helps to inform the mechanisms behind optimal assignment policy design (Carrell et al., 2013) and mindset-based interventions (Alan et al., 2019). With these motivations, I study the peer effect of persistence, a personality trait that reflects the ability to persevere in the face of challenges and setbacks, on students' academic achievement and the underlying mechanisms.

Causal inference in estimating the impact of peer persistence mainly encounters three empirical challenges: selection biases, the reflection problem, and common shocks (Manski, 1993; Angrist, 2014). Selection problems arise if students with similar ability backgrounds sort into the same neighborhood/school/classroom, which makes it infeasible to distinguish the impact of peers' persistence attributes from peers' academic ability on the focal student's academic outcomes. I address selection by exploiting the student-classroom random assignment in middle schools in China, which generates exogenous across-class variations in peer composition. The reflection problem refers to a student and her classmates in the same classroom could affect each other simultaneously when using the current measurement of students, leading to reciprocal causation. To circumvent the reflection problem, I use students' retrospective measures of persistence in Grade 6, one academic year prior to the random assignment. Common shocks indicate the shared environment/influences that students in the same classroom receive in addition to the impact of peer persistence traits. To mitigate the effects of common shocks and hence obtain more precise estimates of peer persistence effects, my empirical specification controls for a host of teacher and peer characteristics.

To estimate the peer persistence effect, I use a nationally representative sample of China's middle school students provided by the China Education Panel Survey (CEPS). CEPS is ideal for this study because it surveys students' retrospective persistence and includes a sample of middle schools that implement random assignments. Alternatively, research can use a self-collected survey with a randomness design, in which a comprehensive investigation might be constrained by the relatively small set of survey items in the questionnaire. The CEPS surveys various information from 19,487 students from Grades 7 and 9, their parents, teachers, and principals from 112 schools in 28 counties in China. Grade 7 students were first surveyed in the school year 2013-14, and then followed up when they moved to Grade 8. Given the richness of information contained in the CEPS, my study can observe changes in students and individuals around them in different dimensions and over time, thereby providing insights into the impact of peer persistence and the potential mechanisms.

I find positive impacts of peer persistence on students' achievement in both baseline and follow-up waves. Students' achievement-relative skills, including self-assessment and cognitive scores, also improve in the follow-up wave. By interacting with students' baseline persistence, the heterogeneity reveals that the improvement of academic achievement is mainly concentrated among students with medium and high persistence, indicating a complementary relationship between students' own persistence and peer persistence in improving achievement.

I investigate three mechanisms that could underlie the impact of peer persistence: students' own persistence and behavioral changes, teacher response, and endogenous friendship formation. When looking at student response, results show higher persistence of peers increases the focal student's persistence. Consistently, students' perseverance-related attitudes also improve – students agree that they can adjust themselves quickly when experiencing mental stress and they are more likely to aspire to obtain a college degree. Associated with the changes in persistence and attitudes, students also adopt more self-disciplined behaviors, as measured by decreases in both tardiness and truancy. In

turn, these self-disciplined behaviors improve the overall classroom environment. Next, when looking at teacher responses, I find that both students and parents are more likely to have perceptions that teachers are more responsible and patient. In addition, teachers' self-reported time spent in teaching preparation also increases. Lastly, by examining students' friendship networks, I uncover that having more persistent peers in the classroom increase the likelihood that students make friends with "good" peers who perform well academically and avoid making friends with "bad" peers who misbehave.

The contribution of my study is twofold. First, it advances the understanding of the role non-cognitive skills played in skill formation technology. Literature has documented the importance of non-cognitive skills by coordinating knowledge from developmental psychology into economics (Heckman and Rubinstein, 2001; Heckman et al., 2006; Borghans et al., 2008; Lindqvist and Vestman, 2011; Almlund et al., 2011; Lavecchia et al., 2016; Heckman et al., 2019). The skill formation technology highlights two parameters: self-productivity and dynamic complementary, which implies current skill could affect future skills through both direct and cross effects (Cunha et al., 2010). While many studies have investigated the impact of the focal student's non-cognitive skills, evidence related to the impact of peers' persistence is scarce. One seminal example and also the most closely related paper is Golsteyn et al. (2021), which studies the impacts of peer personality by exploiting random assignment of students to teaching sections in a college setting. They find that students perform better in the presence of more persistent peers and that this impact endures overtime, consistent with my findings.¹ Compared to Golsteyn et al. (2021), this study makes the following contributions: 1) it generalizes the existing research beyond developed countries and college settings; 2) in addition to traditional academic outcomes, it analyzes other

¹A few other studies also look at the impact of peers' non-cognitive skills. Shure (2021) finds consistent positive impacts of conscientious peers on student achievement in the secondary setting in Belgium, with the identification relying on a school fixed-effects framework. Neidell and Waldfogel (2010) documents negative impacts of peer externalizing behaviors on students' academic outcomes, exploiting the preschool setting and plausible student-classroom random assignment within kindergartens in the US. Bietenbeck (2021) studies the impact of motivated peers on student achievement and long-term outcomes in elementary schools using data and random assignment from Tennessee's Project STAR (Student/Teacher Achievement Ratio). However, none of these studies examine how the persistence traits of peers affect outcomes.

achievement-related outcomes; 3) it provides estimates with external validity by using a nationally-representative sample of middle school students; and 4) it offers additional insights into the underlying mechanisms.²

This study also provides policy implications from two different perspectives. First, the insights into the mechanisms behind the spillover effect of persistence help open the black box of the recent mindset-based intervention literature (Damgaard and Nielsen, 2018; Bettinger et al., 2018; Alan et al., 2019). The literature mainly focused on assessing the direct effects without accessing spillovers. If there are spillover effects, the implications of such interventions become even more salient. My findings of how peer persistence affect the focal student’s persistence help researchers and policymakers to better understand and design mindset-based interventions. Second, my study helps for researchers rethink peer-based optimal policy design. Carrell et al. (2013) show how a failure to account for the endogenous friendship formation could lead to inefficient design in the peer-based optimal policy. My study provides empirical evidence illustrating how persistence *homophily* would lead to endogenous friendship formation, thereby affecting the channel behind peer effects in skill formation.

The paper is organized as follows. Section 2 introduces the student-classroom random assignment and data. Sections 3 and 4 present the identification strategy and main findings. Section 5 discusses mechanisms and Section 6 concludes.

2 Randomization Background and Data

The K-12 education system in China now comprises six years of primary school (Grades 1 to 6), three years of junior high school (Grades 7 to 9), and three years of senior high school (Grades 10 to 12). The Compulsory Education Law (CEL), which was introduced in 1986, aims at providing students with nine years of compulsory education, covering primary and

²Broadly, this study also speaks to the peer effects studies in the economics of education literature (see Sacerdote (2011) and Cools and Patacchini (2021) for two surveys.)

junior high school.³

In 2006, the Compulsory Education Law underwent revisions that encompassed financial protection for compulsory education as part of the government’s educational provisions. The revised law stipulated that students in compulsory education should not be subjected to tuition fees or any additional charges. Additionally, to promote equal and equitable opportunities for all students, the 2006 CEL explicitly prohibited tracking in primary and junior high schools.⁴

In practice, although not all junior high schools have adopted a random assignment policy since 2006, random assignments have gained popularity. This assignment process takes place at the beginning of junior high school (Grade 7), where newly enrolled students are assigned to classrooms through a random selection process. While specific random assignment strategies may vary among schools, I outline two common methods here: i) purely random assignment and ii) “balanced assignment” rule. The former method utilizes a computer program with a randomizer that incorporates student IDs to carry out the randomization process. The latter, known as the “balanced assignment” rule, involves quasi-random assignments that would balance the test scores of incoming students across classrooms.⁵ The “balanced assignment” approach is commonly employed to identify quasi-random variations in peer effect studies conducted through self-collected surveys in middle schools in China (e.g., Carman and Zhang (2012), Feng and Li (2016), and He and Ross (2017)). While assignment details were not surveyed by CEPS, I follow the literature to identify school samples that implement the random-assignment policy.⁶

³See the 1986 Compulsory Education Law of the People’s Republic of China (in Chinese) at https://www.edu.cn/edu/zheng_ce_gs_gui/jiao_yu_fa_lv/200603/t20060303_165119.shtml.

⁴See the 2006 Compulsory Education Law of the People’s Republic of China (in Chinese) at http://www.gov.cn/flfg/2006-06/30/content_323302.htm.

⁵An example of “balanced assignment” is the following scenario with five classes and 200 students in Grade 7. Based on the baseline test scores of these 200 students, the school ranks them from 1 to 200. Starting with the top five students, the school assigns the student ranked 1 to Class 1, the student ranked 2 to Class 2, the student ranked 3 to Class 3, and so on, until the student ranked 5 is assigned to Class 5. Then, the student ranked 6 is assigned to Class 5, the student ranked 7 to Class 4, and the process continues until the student ranked 10 is assigned to Class 1. The school continues this Z-pattern process until all students are assigned to a classroom.

⁶This method has been widely used in peer effects studies that employ CEPS data. See Hu (2015); Gong

I detail the data, sampling process, and definitions of variables below.

I draw on the China Education Panel Survey to study the impact of peer persistence on student achievement. Conducted by the National Survey Research Center at the Renmin University of China, CEPS is a longitudinal survey on a large scale and with a national representative. CEPS employs the PPS (probability proportional to size)-based stratified and multistage sampling design to collect nationally representative of their surveyed sample. The sampling process first selects county-level divisions (henceforth, county) and then selects middle schools within the counties.⁷ Two classrooms from Grades 7 and 9 were drawn from all selected middle schools. All students in the drawn classrooms, as well as their parents, teachers, and the school principal, are surveyed by the CEPS.⁸

In the first wave, CEPS surveyed about 19,487 7th- and 9th-grade students in the 2013-14 academic year from 438 classrooms of 112 middle schools in 28 counties in China. In the follow-up wave, all Grade 7 students were followed when they moved to Grade 8, while Grade 9 students were not followed as they were a pilot sample. To date, the CEPS has only released the first two waves. Since I use retrospective measures of persistence, I did not consider 9th-grade students to avoid recall errors. My sample thus consists of 7th-grade students in the baseline and follow-up waves.

To select school samples that implement random assignment in CEPS, I adopt criteria similar to those used by [Gong et al. \(2018\)](#). Middle schools are identified as randomly assigning their students to classrooms if they meet two conditions: (i) the school principal reports that random assignment is used to arrange new students into classrooms; and (ii) all headteachers report that students are not assigned by test scores. I further drop schools if the principal in wave two reports re-assignment of students into classrooms when 7th-grade students move to 8th grade. This leads to 49 schools remaining, 43.8% (49 out of 112) of

et al. (2018); [Eble and Hu \(2019, 2020\)](#); [Hu \(2018\)](#); [Gong et al. \(2019\)](#); [Xu et al. \(2022\)](#); [Chung and Zou \(2023\)](#), among others.

⁷China's administrative division system has the following order: central (1st), province (2nd), prefecture (3rd), county (4th), and township (5th).

⁸See details of CEPS at <http://ceps.ruc.edu.cn/English/Overview/Overview.htm>.

the school sample.

After selecting school samples, I keep students whose key variables (i.e., student achievement and control variables of students, peers, and headteachers) are not missing. Since the variation comes across the two surveyed classrooms within each school-grade cell, I also drop 4 schools that have only one Grade 7 class. In the end, I obtain a final estimation sample of 3,051 students across 90 classrooms in 45 schools, with their demographic variables and outcomes in both waves, as well as information on their parents and teachers.

The following variables are selected to study the impact of peer persistence on student outcomes.

Persistence.— Persistence is a personality trait related to Conscientiousness under the Big Five personality model. Persistence reflects the extent of hard-working by students and their ability to persevere when facing challenges and setbacks, which is strongly correlated with *grit* (Credé et al., 2017). Persistent people tend to be achievement-oriented, self-disciplined, and predictive of success in academic performance (Duckworth et al., 2007; Duckworth and Gross, 2014; Hagger and Hamilton, 2019).

In the CEPS wave one, students were asked about seven questions related to their retrospective personality traits in Grade 6 are measured. I follow the Big Five model, one of the main models in Psychology, to classify these seven questions into different personality categories.⁹ The first three measures students’ retrospective persistence in Grade 6, asking students to indicate their level of agreement with each statement about their experiences in Grade 6 on a Likert scale ranging from 1 (totally disagree) to 4 (totally agree). The three statements are as follows: 1) “Even if I was not feeling very well or had other reasons to stay at home, I would try my best to go to school”; 2) “Even for the homework that I dislike, I would try my best to finish it”; and 3) “Even if the homework would take me quite a long time to finish, I would try my best to finish it”. To better interpret the measure, I

⁹The CEPS collects the seven question items on personality traits without providing specific guidance. I thank Brent W. Roberts, a personality psychologist at the University of Illinois Urbana-Champaign, for his help to identify the relationship between these seven items and the Big Five personality factors - Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

standardize each item over the estimation sample to obtain a mean of zero and a standard deviation (SD) of one, then take the average of the three standardized items to construct a persistence index, and normalize the averaged index again.

The persistence scale in CEPS is similar to that used in [Golsteyn et al. \(2021\)](#), which originates from the Student Motivation Scale developed by psychologists in [Martin \(2009\)](#).¹⁰ The similarity between the two persistence measurements provides *criterion validity* to the persistence scale in the CEPS. The similarity also offers unique opportunities to contribute to the economics literature. For instance, one would wonder whether the findings in [Golsteyn et al. \(2021\)](#) among college students in the Netherlands can be replicated among middle school students in another country, and if so, whether my study can provide additional evidence that informs our understanding of the underlying mechanisms.¹¹

The other four questions relate to two other personality factors of the Big Five model, Extraversion and Openness.¹² Since those questions are not valid measurements for Extraversion and Openness or any of their lower facets, I use their average as controls and refer to them as *other noncognitive measures* in Grade 6. Similar to persistence, I standardize items first, then average them, and normalize the averaged index over the entire estimation sample in the end.

Student Outcomes.— To measure student achievement, I draw on the midterm test scores for the three core subjects (Chinese, Math, and English) in Grades 7 and 8. Test scores are obtained directly from the school administrations by the CEPS. In wave one, CEPS standardized the test score to have a mean of 70 and a standard deviation of 10. I standardize

¹⁰In [Golsteyn et al. \(2021\)](#), the persistence scale consists of four question items rated on a scale from 1 to 7 (see Table 2 on p.1063). The items are as follows: 1) “If I can’t understand my university work at first, I keep going over it until I do”; 2) “If my homework is difficult, I keep working at it trying to figure it out”; 3) “When I’m taught something that doesn’t make sense, I spend time trying to understand it”; and 4) “I’ll keep working at difficult university work until I think I’ve worked it out.”

¹¹One remaining issue is the use of retrospective measures. For example, students with different abilities could recall their persistence in Grade 6 differently, and the persistence measurements may be a function of students’ status in Grade 7. I discuss and address this concern in Section 4.3.

¹²CEPS ask students “How much do you agree with each of the following statements about your experiences in Grade 6?” with a scale from 1 to 4 on the following four questions: 1) “I was able to express myself clearly”; 2) “I was able to give quick responses”; 3) “I was a fast learner”; 4) “I was curious about new stuff”. Items (1) and (2) relate to Extraversion, while items (3) and (4) related to Openness.

the test scores by school-grade-subject level to have zero mean and unit standard deviation in order to interpret estimates. In wave two, the raw test scores of each student and the total score of each subject are provided within each school-grade-subject block. Again, to facilitate interpretation, I scale the raw test score with the total score for each student first and then normalize the scaled score over the estimation sample.

In addition to achievement, I use three non-achievement outcomes of students, including students' self-assessment on each subject, cognitive assessment scores, and mental stress.

For self-assessment on each subject, CEPS asks students "whether the following courses were difficult for you in Grade 7?" for the three subjects with a scale from 1 (very difficult) to 4 (not difficult at all). I standardize each item, take the average of the three items, and then standardize the average to have a zero mean and unit standard deviation over the estimation sample. Estimated impacts on self-assessment of each course can complement the results found on students' achievement. For example, if peer persistence has an impact on improving test scores, we would expect to find improvements when looking at the self-assessment.

The cognitive score is obtained from a standardized cognitive assessment test, developed and implemented by the CEPS. The cognitive score is assessed for all surveyed students, providing a universal comparison. The cognitive test assesses students' general ability and not the specific knowledge students learned.¹³ I use the standardized cognitive scores directly provided by the CEPS, which are generated via a three-parameter logistic (3PL) model. The investigation of cognitive scores is also informative, given that the cognitive assessment captures parts of, if not a general pattern of, students' ability formation. Thus, we also expect increases in students' cognitive scores, when there are improvements in student achievement.

In addition to student achievement-related outcomes, I examine whether students' mental stress is affected by peer persistence. Following [Gong et al. \(2019\)](#), I use four questions in both waves to measure mental stress. The CEPS asks students "do you have the feelings

¹³The cognitive test assesses students' cognition via three dimensions: verbal; graphical and spatial; and computational and logical. The construction of the cognitive assessment is following those of the Taiwan Education Panel Survey ([Wang and Lei, 2015](#)).

below in the last seven days?” with a scale from 1 (never) to 5 (always): (1) depressed, (2) blue, (3) unhappy, or (4) that life is meaningless.¹⁴ Again, I first normalize each item over the entire estimation sample, then average the normalized four items, and normalize the averaged index over the estimation sample again. Examinations of mental stress provide a fuller picture of the evaluation of peer persistence effects, because there might be differential effects when looking at the impact of peer persistence on the formation of skills in different dimensions. For example, having more persistent peers in the classroom could improve the focal student’s achievements while harming her mental health.

Control Variables.— I choose a set of students’ predetermined variables as the student controls. The control variables include the student’s age, gender, ethnicity, rural status, local residency status, number of siblings, whether attended kindergarten, age attending primary school, parent’s years of schooling, and persistence and other noncognitive measures in Grade 6. These predetermined variables are used to implement balancing tests, and are also included in estimations to improve estimation precision. Table 1 provides the statistical description.

I also include controls from teachers and peers. Given that the assignments also generate across-classroom teacher variations within each school-grade cell, including teacher controls will help to account for the impacts of teachers on student outcomes. The teacher controls include headteachers’ age, gender, marriage status, whether they have a college degree, and years of teaching experience.¹⁵ Finally, I incorporate peer controls to account for potential impacts from peers on student outcomes. These peer controls include leave-me-out averages of female peers, migrant peers, low-achieving peers, and college-educated peer mothers.¹⁶

¹⁴In wave two, CEPS asks students “blue” with a slightly different description – “blue and thus cannot focus”.

¹⁵I also use the same controls at the subject teacher level later in a robustness check.

¹⁶There are studies showing the impact of female peers (Hu, 2015; Gong et al., 2019), migrant peers Hu (2018), low-ability peers (Xu et al., 2022), peer maternal education (Chung and Zou, 2023) on student outcomes, using the same data and identification strategy.

Table 1: Summary Statistics

	All	
	Mean	SD
A. Outcome variables		
Test score in Grade 7	70.601	9.538
Test score in Grade 8	70.582	9.588
B. Variables of interests:		
Persistence in Grade 6	3.470	0.624
peers' persistence	3.470	0.168
C. Control variables:		
Student age	13.418	0.612
Female student	0.498	0.500
Minority	0.072	0.258
Agricultural Hukou	0.370	0.483
Nonlocal residence	0.209	0.407
Sibling size	0.502	0.709
Attend kindergarten	0.865	0.342
Age attending primary school	6.692	0.926
Repeat grade in primary school	0.075	0.264
Parents' years of schooling	11.594	3.204
Non-cognitive measures in Grade 6	3.271	0.573
Observations[#]	3,051	

Notes. The table displays means and standard deviations (SD) for the estimation sample. The raw values of total scores, persistence and non-cognitive measures in Grade 6, and averages of peers' persistence are presented in this table, whereas the regression analysis utilizes the standardized values of these variables.

[#] Observation in Panel A is 9,153, which includes students' test scores in the three subjects.

3 Identification Strategy

This section presents identification strategies for assessing the exogeneity of across-class peer variations (i.e., balancing tests) and estimating the impact of peer persistence (i.e., linear-in-mean model), followed by a battery of tests validating the student-classroom random assignment.

3.1 Balancing Tests

I first verify the student-classroom random assignments via balancing tests using the following equation:

$$\overline{\text{PeerPersistence}}_{i,j,k} = \beta_0 + \beta_1 X_{i,j,k} + \delta_k + \epsilon_{i,j,k} \quad (1)$$

where $\overline{\text{PeerPersistence}}_{i,j,k}$ is the leave-me-out average of peer persistence in class j within school-grade k . $X_{i,j,k}$ is the set of students' predetermined variables, including student age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, parents' years of schooling, and non-cognitive measures in Grade 6. δ_k is the school-grade fixed effects.¹⁷ ϵ_i is the error term, which is clustered at the grade-by-school level, the level of random assignment.

The intuition behind this balancing test is straightforward. Without school-grade fixed effects, a student's predetermined variables should correlate with the average of her peers' persistence, indicating characteristic-based sorting of students. However, when students were randomly assigned into classrooms within each school-by-grade cell, conditional on the grade of school a student is attending (i.e., including school-grade fixed effects), there should be no correlation between students' predetermined variables and peer persistence average. In addition to this balancing exercise, I perform a battery of alternative checks to confirm the

¹⁷Since only 7th-grade students are used in this study, the school-grade fixed effects are identical to the school fixed effects. However, to avoid confusion, I use "grade-by-school" to refer to the level of random assignment throughout the paper.

randomness used for identification in section 3.3 below.

3.2 Linear-in-Mean Model

To examine the peer effects of persistence on student achievement, I use the following linear-in-mean model:

$$Y_{i,s,j,k} = \beta_0 + \beta_1 \overline{\text{PeerPersistence}}_{i,j,k} + \beta_2 X_{i,j,k} + \beta_3 T_{i,j,k} + \beta_4 P_{i,j,k} + \delta_{s,k} + \epsilon_{i,s,j,k} \quad (2)$$

where $Y_{i,s,j,k}$ is the test score of student i in subject s in class j and grade-by-school k . The equation pools standardized test scores of the three subjects together and estimates the impacts of peers' persistence within each school-grade-subject cell as indicated by $\delta_{s,k}$. The estimation uses student achievement in both baseline (Grade 7) and follow-up waves (Grade 8). $X_{i,j,k}$ is the same set of students' predetermined variables. To further control for the impact of teacher and other peer characteristics on student achievement, the specification includes teacher controls $T_{i,j,k}$ and peer controls $P_{i,j,k}$. The teacher controls include headteachers' age, gender, teaching experience, and dummy variables indicating marital status, and having a college degree or above. Peer controls include the leave-me-out average of female, migrant, and low-ability peers, and peer mothers with a college degree. Standard errors are clustered at the grade-by-school level, allowing correlations across students within each school-grade cell.

In addition to academic achievement, the linear-in-mean model is also used to estimate the impact of peer persistence on students' non-achievement outcomes (self-assessment, cognitive test scores, and mental stress), as well as mechanism variables. In these analyses, comparisons are performed at the student level within each school-by-grade cell.

3.3 Tests for Random Assignment

Before performing the balancing test, I check if there is sufficient variation in class-level persistence average, both unconditional and conditional on each school-grade cell. Figure 1 shows the unconditional averages of class-level persistence over different classes (Figure 1a) and the associated histogram (Figure 1b). The figures verify that there is sufficient variation in class-level persistence means in general. In line with the research design, Figure 2 plots the scatter dots of persistence averages across the two classrooms within each school-grade block (Figure 2a) and the associated histogram of the within school-grade differences (Figure 2b). When classroom assignments fail to generate enough differences in the persistence averages across classrooms, we would observe that most of the dots in Figure 2a are close to the 45-degree red line. However, Figure 2a reveals large different differences in persistence means across the two classrooms, leading to deviations from the 45-degree line. Figure 2b shows that the within-grade across-class differences of persistence means range from 0.004 to 0.521, and none of the dots are on the red 45-degree line, indicating sufficient identifying variations.

Though other researchers in the literature have validated the employed identification strategy, I formally assess the randomness of the within-grade peer persistence variations, by conducting the balancing tests in Table 2. Column (1) shows the correlations between peers' persistence and students' predetermined variables unconditional on school-grade fixed effects. Sorting with higher persistent peers is positively associated with students being in a lower socioeconomic status (e.g., having an agricultural *hukou* and less educated parents), more likely to be local residences, and having higher persistence and other noncognitive measures in Grade 6. Without adding school-grade fixed effects, student sorting could occur across schools or classrooms, which would make the results hard to be interpreted. Column (2) presents the corresponding results with school-grade fixed effects. Conditional on the attended school and grade, none of the student's time-invariant variables is correlated with her peers' persistence average, indicating a good balancing for the within-grade peer persistence variations. The Column (2) results also show the virtue of the random assignment

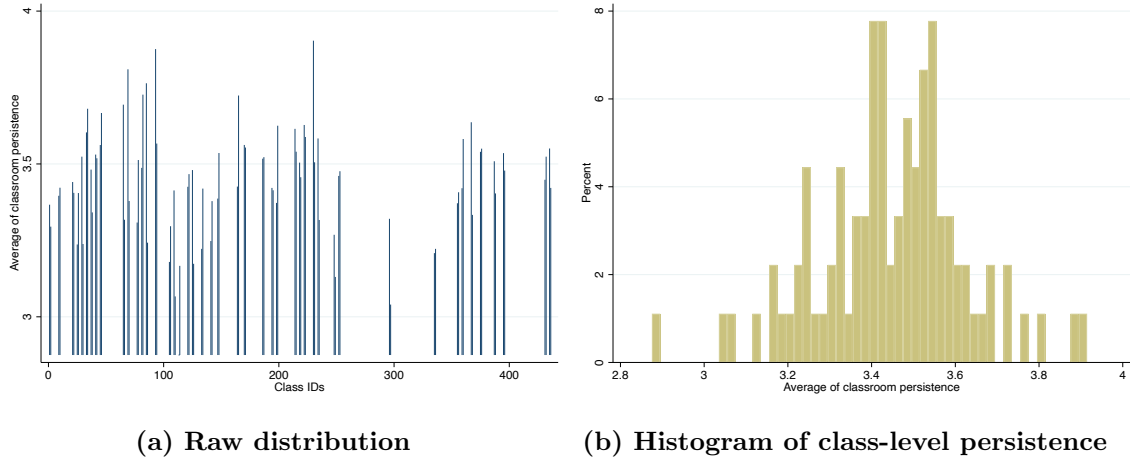
used in this study, which addresses the sorting issues observed in Column (1).¹⁸

To provide additional balancing validation, I conduct two other checks. One is a balancing test at the classroom level, which regresses the class-level persistence mean on a headteacher's predetermined variables, unconditional and conditional on the school-grade fixed effects. The robust balancing results are in Appendix Table A2.

The second check is a permutation test. The permutation test consists of three steps: 1) reshuffling the student samples in the estimation sample and re-assigning them into two classrooms randomly within the grade; ii) comparing the class-level means of students' predetermined variables between the original versus newly-generated classrooms; 3) repeating the above two steps 10,000 times and calculating the p-value for each characteristic based on the probability of having the simulated mean lower than the actual one. The idea behind the permutation test is intuitive. If the original student-classroom assignment was not random but based on students' ability/characteristics, then after reassigning students randomly into the two new hypothetical classrooms, the simulated class-level mean of student characteristics should differ statistically from the original actual mean. The results of permutation tests are in Appendix Table A3, which shows that the p-values of most variables are close to 0.5. The p-values range between 0.288 and 0.510, well above 0.05 cutoff to reject the null hypothesis that students were randomly assigned to each classroom within each school-grade unit. Taken together, the two checks validate the identifying assumption of the student-classroom random assignment reported by school administrators.

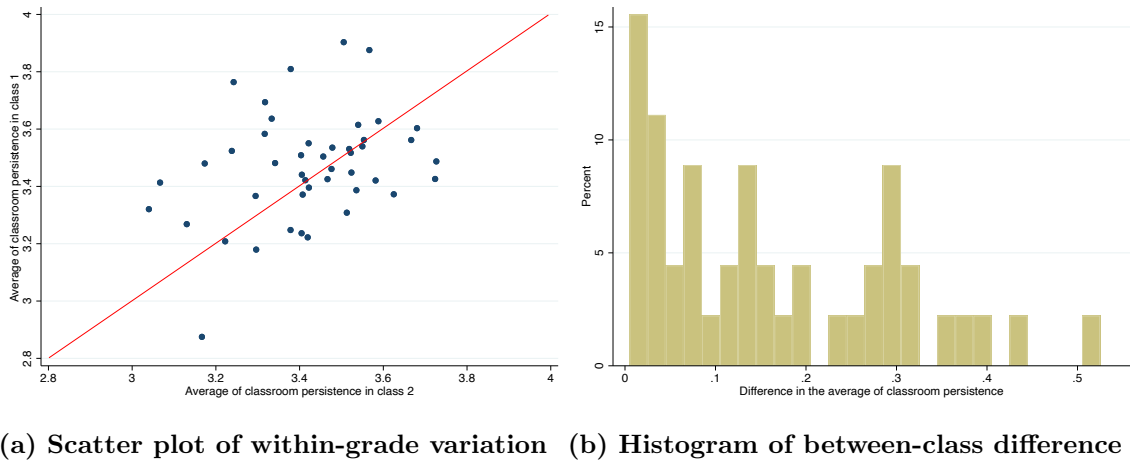
¹⁸Alternatively, one can perform balancing tests that regress one predetermined variable of students on their peers' persistence mean, without and with school-grade fixed effects. This balancing test is provided in Appendix Table A1, which shows a similar balancing pattern and endorses the identification.

Figure 1: Variation of class-level persistence



Note. Figure 1a shows the raw distribution of the average of class-level persistence. Figure 1b plots the histogram of the class-level persistence average (shown in 0.02 bins). The persistence average of a class ranges from 2.875 to 3.903.

Figure 2: Variation of class-level persistence within each school-grade cell



Note. Figure 2a plots the average of class-level persistence across two classes within each school-grade cell. Figure 2b plots the histogram of differences between the persistence average in the two classes within each school-grade cell (shown in 0.02 bins). The within-school-grade differences of class-level persistence average range from 0.004 to 0.5212, with all of the class pairs having values that differ from zero.

Table 2: Balancing Test for Random Assignment

	peers' persistence	
	(1)	(2)
Student age	-0.003 (0.009)	0.004 (0.005)
Female student	-0.003 (0.008)	0.001 (0.005)
Minority	-0.004 (0.029)	0.001 (0.010)
Agricultural Hukou	0.049** (0.019)	-0.010 (0.008)
Non-local residence	-0.093*** (0.024)	-0.004 (0.008)
Sibling size	-0.014 (0.013)	-0.002 (0.006)
Attend kindergarten	-0.010 (0.017)	-0.008 (0.011)
Age attending primary school	0.016* (0.009)	0.001 (0.003)
Repeat grade in primary school	0.006 (0.032)	-0.021 (0.012)
Parents' years of schooling	-0.009** (0.003)	-0.000 (0.001)
Persistence in Grade 6	0.022*** (0.008)	-0.005 (0.005)
Non-cognitive measures in Grade 6	0.014** (0.006)	0.004 (0.003)
School-grade FE		✓
Observations	3,051	3,051

Notes. Each column represents a separate regression that regresses the peers' persistence on students' pre-determined variables. Regression in Column (2) includes school-grade fixed effects. Robust standard errors clustered at the school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4 Main Findings

In this section, I investigate the impact of peer persistence on students' achievement and non-achievement outcomes (self-assessment, cognitive scores, and mental stress). Following the baseline results, I address potential concerns with robustness checks and explore heterogeneous effects.

4.1 Impacts on Academic Achievement

Table 3 shows the impact of peer persistence on student achievement. Panels A and B look at students' achievement in Grades 7 and 8, respectively. Column (1) only includes school-grade fixed effects, while columns (2) to (4) gradually introduce the students' predetermined variables, teacher characteristics, and peer controls to gain more precise estimates.

Results in Panel A indicate that having classmates with higher persistence improves student achievement in Grade 7. This finding holds across specifications when more controls are included. The magnitudes decline from 0.114 in Column (1) to 0.095 in Column (4), with the significance level remaining at 1%. Adding teacher and peer controls accounts for 12.8% of the reduction in magnitudes between Columns (2) and (4), indicating the importance of addressing common shocks. For the preferred specification in Column (4), a one standard deviation increase in peers' persistence leads to a 0.095 standard deviation increase in standardized total scores at the baseline.

In addition to the positive effects on student achievement in Grade 7, Panel B examines the impact of peers' persistence on test scores in Grade 8. As shown in Columns (1)-(4), including more controls, in general, improves the estimation precision. Results in Column (4) show a one standard deviation increase in peers' persistence leads to a 0.127 standard deviation increase in total scores at the follow-up wave, which finds a slightly larger magnitude than the one at the baseline. The results imply a lasting impact of peers' persistence on student achievement that increases with duration of exposure. The lasting

effect is consistent with the channel of friendship network discussed later, which takes time to form and develop.

To provide insights into the underlying drivers, Table A4 looks at the impact on each individual subjects. Results in Panel A show that Math and English underlie the overall effect on student achievement at the baseline. Panel B shows there are also improvements in Chinese test scores, which become the driving forces that lead to increased academic performance in the follow-up wave.

I also check whether there is an impact on students' non-achievement outcomes. Verifying impacts on achievement-related outcomes is informative for baseline findings. For example, students' self-assessment and cognitive ability are likely to be affected when students are observed to perform better on achievement-based measures, indicating a general formation of skills. I also test impacts on mental stress, a focus of the literature that is not in the cognitive domain.

The three outcomes are tested in Appendix Table A5, with linear-in-mean estimates shown in Panel A. Columns (1)-(2) reveal that students have higher self-assessments when they are around more persistent peers. Students with more persistent peers also have higher cognitive scores at baseline, though the difference is not significantly different from zero (Column 3). However, the improvement in cognitive assessments grows becoming significantly different from zero when students move to Grade 8 (Column 4). In the end, Columns (5)-(6) show peers' persistence has no impacts on students' mental stress, indicating that improvements in achievement do not come at the expense of harming students' mental health.

Table 3: Impacts of Peers' Persistence on Student Achievement

	Std. test score			
	(1)	(2)	(3)	(4)
Panel A. Grade 7				
Peer persistence	0.114*** (0.035)	0.109*** (0.034)	0.099*** (0.031)	0.095*** (0.029)
Own persistence	0.138*** (0.015)	0.095*** (0.013)	0.094*** (0.013)	0.094*** (0.013)
R-squared	0.023	0.097	0.099	0.103
Panel B. Grade 8				
Peer persistence	0.138*** (0.034)	0.134*** (0.033)	0.122*** (0.029)	0.127*** (0.027)
Own persistence	0.149*** (0.015)	0.100*** (0.013)	0.099*** (0.013)	0.099*** (0.013)
R-squared	0.028	0.109	0.110	0.114
School-grade-subject FE	✓	✓	✓	✓
Student controls		✓	✓	✓
Teacher controls			✓	✓
Peer controls				✓
Observations	9,153	9,153	9,153	9,153

Notes. The dependent variables are total scores standardized within each school-grade-subject cell, to obtain a zero mean and one standard deviation. Panels A and B use the test scores of students in Grades 7 and 8, respectively. 'Peer persistence' refers to the leave-one-out average of classmates' persistence, while 'Own persistence' is students' persistence in Grade 6. Both 'Peer persistence' and 'Own persistence' are standardized over the estimation sample to have a zero mean and one standard deviation. The student controls include age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, whether repeat grade in primary school, and non-cognitive measures in Grade 6. The teacher controls include the headteacher's age, gender, teaching experience, and dummy variables indicating marital status, and having a college degree or above. Peer controls include the classroom proportion of female, migrant, and low-ability peers, and peer mothers with a college degree. Robust standard errors clustered at the school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2 Heterogeneous Effects

While the linear-in-mean framework captures the average treatment effect behind the exogenous variations of peer persistence, heterogeneity analyses can unmask the potential heterogeneous effects for students with different backgrounds.

To estimate the heterogeneous effect of peer persistence, I use equation (3) below which interacts the peer persistence average with students' baseline persistence. I first divide students into three groups by tercile based on their baseline persistence: low, medium, and high persistence. Then I obtain the interaction terms between peer persistence and the three indicators. Replacing the peer persistence and students' own persistence in equation (2) with the three interaction terms and the three indicators yields the following specification:

$$\begin{aligned}
 Y_{i,j,k} = & \beta_0 + \sum_{g \in \{L,M,H\}} \gamma^g \cdot \text{Persistence}_{i,j,k}^g * \overline{\text{PeerPersistence}}_{-i,j,k} + \sum_{g \in \{L,M,H\}} \phi^g \cdot \text{Persistence}_{i,j,k}^g \\
 & + \beta_2 X_{i,j,k} + \beta_3 T_{i,j,k} + \beta_4 P_{i,j,k} + \delta_k + \epsilon_{i,j,k}
 \end{aligned} \tag{3}$$

where $Y_{i,j,k}$ are student's academic and non-academic outcomes in Grades 7 and 8. $\sum_{g \in \{L,M,H\}} \text{Persistence}_{i,j,k}^g$ is the group of three indicators measuring student i 's baseline persistence with level $g \in \{\text{Low}, \text{Medium}, \text{High}\}$, with low persistence omitted as the reference group. $\text{Persistence}_{i,j,k}^g * \overline{\text{PeerPersistence}}_{-i,j,k}$ are the interaction terms between peer persistence and the three indicators. γ^g are parameters of interest that reflect the heterogeneous effects. The remaining terms are the same as in equation (2).

Table 4 shows the heterogeneous effects of peer persistence on students' academic outcomes. In Grade 7, medium- and high-persistence students benefit more from persistent peers in achieving better academic performances. The F -statistics show that the gains of high-persistence students from their persistent peers significantly exceed those of students with a low persistence (p -value = 0.0132). Though the magnitude of "peer persistence*medium (persistence)" is larger than "peer persistence*low (persistence)", they

are statistically indistinguishable from each other.

In the follow-up academic year in Column (2), while medium- and high-persistence students contribute to benefit from having higher-persistence peers, students with low persistence also begin to benefit as well. The achievement gains of these low persistence students partially explain the overall improvement found in the baseline results when students are in Grade 8. Gains of high-persistence students from their peers still significantly exceed those of low-persistence students (p -value = 0.0809).

The results suggest a complementary relationship between high-persistence students and having more persistent peers in improving student achievement. The complementary relationship could be driven by *homophily* – students who share similar characteristics (e.g., persistent personality traits or good academic performance) are more likely to interact with each other, leading to improvements in achievement.

Panel B of Appendix Table A5 looks at the heterogeneous effect of peer persistence on students' non-achievement outcomes. The heterogeneous effect on self-assessments exhibit a similar pattern to that of academic achievement. Low-persistence students exhibit null effects in the baseline, but gain from persistent peers in the follow-up wave, improving the overall average effect size (Columns 1-2). Cognitive scores do not significantly differ from zero in the baseline and then increase significantly in the follow-up wave (Columns 3-4). Columns (5)-(6) show no heterogeneous effects on mental stress, indicating that the null effect found in the linear-in-mean model is unlikely to reflect offsetting heterogeneous treatment effects of opposite signs from students with different backgrounds.

Table 4: The Heterogeneous Effects of Peers' Persistence on Student Achievement

	Std. test score	
	Grade 7 (1)	Grade 8 (2)
Peer persistence*low persistence	0.052 (0.037)	0.100*** (0.035)
Peer persistence*medium persistence	0.082** (0.034)	0.107*** (0.032)
Peer persistence*high persistence	0.120*** (0.028)	0.145*** (0.028)
<i>P-value of test of hypothesis</i>		
Peer persistence*high = Peer persistence*low	0.0132	0.0809
Peer persistence*high = Peer persistence*medium	0.1119	0.1350
Peer persistence*medium = Peer persistence*low	0.2979	0.8008
School-grade-subject FE	✓	✓
Student controls	✓	✓
Teacher controls	✓	✓
Peer controls	✓	✓
R-squared	0.107	0.118
Observations	9,153	9,153

Notes. The dependent variables are total scores standardized within each school-grade-subject cell, to obtain a zero mean and one standard deviation. 'Peer persistence' is interacted with a dummy group of students' own persistence to assess the heterogeneous effect. 'Peer persistence' is standardized over the estimation sample to have a zero mean and one standard deviation. The P-value of F-statistics tests the null hypothesis on if estimates between the two interaction terms are indifferent. The student controls include age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, whether repeat grade in primary school, and non-cognitive measures in Grade 6. The teacher controls include the headteacher's age, gender, teaching experience, and dummy variables indicating marital status, and having a college degree or above. Peer controls include the classroom proportion of female, migrant, and low-ability peers, and peer mothers with a college degree. Robust standard errors clustered at the school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3 Addressing Potential Concerns

I now address two concerns regarding the benchmark estimations: the use of retrospective persistence measure and the lack of baseline academic ability as a control in the estimations.

One might worry about measurement errors when using retrospective persistence in the estimation. For example, students with certain characteristics (e.g., having a good memory at the baseline, being more confident in their baseline skills) could be more likely to better recall their true persistence, and these characteristics could also affect academic outcomes. If this concern is valid, then the constructed average of peer persistence would be a function combining peers' baseline persistence and other skills, confounding the estimations.

However, this is unlikely to be the case. The retrospective persistence measure has a scale between 1 and 4, which does not require students to have a good memory to recall some exact detailed numbers/records. Consistently, as shown in the Appendix Table [A1](#), conditional on school-grade fixed effects, the peer persistence average does not correlate with any of the students' observable characteristics, including personality measures in Grade 6.

To further validate my use of retrospective persistence, I conduct a falsification test that regresses the focal student's retrospective self-assessments in Grade 6 on peer persistence. If retrospective persistence contains certain skills that lead to positive peer persistence effects on student outcomes (e.g., 7th-grade self-assessment), then these skills would also likely be correlated with retrospective self-assessment in Grade 6. However, Panel A of Appendix Table [A7](#) shows peer persistence variations are not associated with any of the students' baseline self-assessments. Taken together, these results indicate that retrospective persistence is unlikely to combine with a student's other skills that would confound the estimations.

Another possible concern with the use of retrospective persistence is the possibility that it may reflect the classroom environment, when they are surveyed in Grade 7. If so, our estimation of the impact of peer persistence would have a reflection problem. To address the possibility, I directly test whether there is a relationship between peers' characteristics and

each of the retrospective persistence items. Each estimate in Panel B of Appendix Table [A7](#) is obtained from a separate regression that regresses one of the 6th-grade persistence items on each of the peer controls – the leave-me-out average of female peers, migrant peers, low-achieving peers, and college-educated peer mothers. Though the proportion of migrant peers and the retrospective persistence on school attendance is correlated significantly at the level of 10%, there is no systematic relationship between peer characteristics and retrospective persistence items across the rest of all regressions. Overall, results in Appendix Table [A7](#) mitigate concerns with the use of retrospective persistence measure.

Another potential concern relates to how failure to control unobservable variables, such as the abilities of incoming students, might bias baseline estimates. A shortcoming of the CEPS is its lack of students’ baseline test scores. Relevantly, we would need to consider how lacking baseline academic abilities could lead to estimation biases (e.g., upward biased). Although my study controls for almost all students’ predetermined characteristics that are available in CEPS, formally, I now assess this concern by conducting bounding exercises below.

I first examine the coefficient stability by including additional ability-related controls. Column (1) of Appendix Table [A6](#) replicates the baseline estimation. In Columns (2) and (3), the regressions separately add one control proxy for the focal student’s baseline academic ability (self-assessment in Grade 6) and one control for peers’ ability (leave-me-out average of accelerated peers who ever skipped a grade in the primary school). The estimates are fairly stable across the specifications with these additional ability controls.¹⁹

However, as [Oster \(2019\)](#) discusses, the coefficient is stable could be due to the additional controls being less important in explaining students’ achievement, rather than being indicating the bias is small. Inspired by [Altonji et al. \(2005\)](#), [Oster \(2019\)](#) proposes a

¹⁹In Columns (4) and (5), I assess the importance of subject teacher controls, using a sample with no missing values in all subject teacher controls. Column (4) follows the same specification as the baseline one, and column (5) uses subject teacher controls. Comparing estimates across the last two columns, test scores in Grade 7 drop slightly when using subject-teacher controls, indicating that achievement improvements may partially reflect the subject-teacher characteristics. However, Panel B reveals no large changes when looking at the impact on 8th-grade test scores, indicating the robustness of the results.

consistent estimator to improve the assessment by incorporating movements in R -squared. The underlying intuition is straightforward: only considering changes in coefficient is not informative enough, and one can infer the coefficient stability by scaling the magnitude changes by movements in R -squared. The coefficient stability test is conducted using two key parameters: the relative importance of selection on unobserved versus observed variables (denoted as δ) and a hypothetical R^2 from the regression with all observed and unobserved variables controlled (denoted as R_{max}).²⁰

Based on the assumptions above, the coefficient stability is assessed in Appendix Table A6. Column (1) replicates the baseline results and adds two assessments: the ratio of importance (δ) and the effect bound (β). The two measures are obtained with R_{max} being set as 1.3 times the R^2 (the R^2 from the fully controlled specification in Column 1), as suggested by Oster (2019). The obtained R_{max} is 0.134 and 1.485 for academic achievement in Grades 7 and 8, respectively. In Panel A, the δ is 6.1440, indicating the selection on unobserved variables must be 6 times larger than the selection on observed variables to fully explain the estimated effect (i.e., to obtain a null effect size), which means the findings are unlikely to be driven by unobservable factors. Alternatively, we can assess the coefficient stability by calculating an effect bound under the condition that $\delta = 1$ (i.e., equal selection on observables and unobservables). The effect bound in Panel A ranges between 0.095 and 0.250, which does not cover zero, thereby rejecting the null hypothesis of no effects. Panel B shows similar results that validate the coefficient stability, where the selection on unobserved variables must be 7 times larger than the selection on observed variables to fully explain the estimated effect on achievement in Grade 8 ($\delta=7.7271$) and the effect bound never include zero (between 0.127 and 0.314).

²⁰The method imposes a few more assumptions, for example, unobservable components are orthogonal to the observable components. See Oster (2019) Section 3 for theoretical details.

5 Mechanism

So far, I have shown that the focal student performs better in her academic achievement when there are more persistent peers in the classroom. To investigate underlying mechanisms, I examine whether higher peer persistence affects students' own persistence and behaviors, their teachers' response, and endogenous friendship formation.

5.1 Students' Own Persistence and Behaviors

[Alan et al. \(2019\)](#) shows that fostering students' grit improves their academic performance. The authors suggest peer effects as a potential mechanism by which treated students may lead to belief and behavioral changes of other untreated students in the same classroom. Together with the fact that persistence is highly correlated to grit, one potential mechanism behind the impact of peer persistence could come from the increased persistence of the focal student. Relatedly, the student might also change her behaviors when her own persistence is boosted.

To investigate, I first look at whether students' own persistence changes. In the follow-up wave, Grade 8 students were asked about their retrospective persistence in Grade 7 using the same persistence scale.²¹ To examine the impact on own persistence, I first use the same three question items as those in wave one. I examine the impact of peer persistence on each of the three items separately, and look at the impact on an index computed from the average of the three items. Panel A of [Table 5](#) reveals that students become more persistent in the face of unpleasant and and challenging homework, as shown in Columns (1)-(3). A one SD in peer persistence on average increases students' own persistence by a 0.111 SD (Column 4). To obtain an aggregated effect and reduce the chance of false positives, I follow [Kling et al. \(2007\)](#) to estimate the mean effect size (MES).²² The result is robust with multiple

²¹Specifically, CEPS surveys students "how much do you agree with each of the following statements about your experiences in Grade 7?" with a scale from 1 (strongly disagree) to 4 (strongly agree), using the same three questions as those used at baseline and an additional question "I would persist in my interests and hobbies".

²²Intuitively, MSE is a weighted average of treatment effect estimates on different outcome variables.

hypothesis testing addressed, which shows an overall mean effect size of 0.095 SD in Column (5).

In addition to students’ retrospective persistence in Grade 7, I test whether peers’ persistence also affects students’ perseverance-related attitudes. Because persistence refers to students’ perseverance when facing challenges and their inclination to set long-run goals (Duckworth et al., 2007), I use two relevant questions available in the CEPS. The first question asks students the extent to which they agree that “when experiencing mental stress, I can adjust myself quickly” with a scale from 1 (totally disagree) to 4 (totally agree). The second question surveys students on their educational aspirations. I create an indicator that equals one if the student hopes to obtain a college degree (a proxy for long-run educational goals) and zero otherwise. Panel B of Table 5 shows that, when there are more persistent peers, the student is more agree that she can adjust herself quickly when facing mental stress (Column 6) and is more likely to have the education aspiration of obtaining a college degree (Column 7).

Lastly, I investigate whether there are changes in students’ self-disciplined behaviors on school attendance. The CEPS asks two questions related to students’ tardy and truancy behaviors: “How much do you agree with each of the following statements about your school life?” with a scale from 1 (strongly disagree) to 4 (strongly agree): 1. “I am always late for class.” and 2. “I always skip classes.” Results in Panel C of Table 5 show supporting evidence on the impact of peer persistence on decreasing students’ tardy and truancy behaviors.²³ The impacts of peer persistence on students’ increased self-disciplined behaviors are in line with the psychological root of the persistence concept. In the Big Five model, both

Following Kling et al. (2007), to construct MES, I first estimate the treatment effect for each outcome, then standardize them, and then average them. Specifically, the MES of peers’ persistence on outcome k in own-persistence category c is defined as the following: $MES_c = (1/n_c) \sum_{n=1}^{n_c} e_{kc} / \sigma_{kc}$, where n_c is the number of outcomes in category c , e_{kc} is the estimate of the impact of peers’ persistence on outcome k , and σ_{kc} is the standard deviation of the outcome variable of the control group. The standard error and p-value of MES are calculated using the method provided in the Web Appendix B of Kling et al. (2007).

²³One might think about an alternative mechanism that peer persistence could affect students’ study inputs. However, Panel A of Appendix Table A8 shows there is no impact of peer persistence on students’ self-reported time use on study and entertainment.

persistence and self-control are considered as correlative facets with Conscientiousness, the best predictor for student academic performance among the five personality traits (Borghans et al., 2008). There is also evidence from developmental psychological literature suggesting that persistence is correlated with self-control behavior, but performs different roles in improving student’s academic achievement (Duckworth et al., 2007; Duckworth and Gross, 2014).

In addition, more self-disciplined students are in the classroom might create a classroom atmosphere where self-disciplined behavior becomes a norm, which further strengthens the peer effects. To investigate, I use students the extent to which agree “the class atmosphere is good” with the same 1-to-4 scale. As Column (10) shows, classroom atmospheres also improve when there are more persistent peers in the classroom.

Table 5: Students’ Own Persistence and Self-Disciplined Behaviors

Panel A. Own persistence in Grade 7					
	School attendance (1)	Disliked homework (2)	Challenging homework (3)	Average (4)	MES (5)
peers’ persistence	0.057 (0.041)	0.105*** (0.038)	0.124*** (0.043)	0.111** (0.045)	0.095** (0.038)
Own persistence	0.159*** (0.026)	0.187*** (0.024)	0.204*** (0.020)	0.215*** (0.024)	0.184*** (0.020)
R-squared	0.058	0.092	0.099	0.099	–
Observations	3,042	3,042	3,042	3,042	3,042
Panel B. Perseverance-related attitudes			Panel C. Self-disciplined behaviors		
	“When experiencing mental stress, I can adjust myself quickly” (6)	Education aspiration: Having a college degree (7)	Tardy: “I am always late for class” (8)	Truancy: “I always skip classes” (9)	“Class atmosphere is good” (10)
Peer persistence	0.040* (0.022)	0.050** (0.019)	-0.039*** (0.014)	-0.024** (0.009)	0.076* (0.039)
Own persistence	0.058*** (0.020)	0.016* (0.009)	-0.042*** (0.014)	-0.005 (0.009)	0.087*** (0.022)
Mean of dep. var.	3.063	0.764	1.146	1.046	3.324
R-squared	0.085	0.144	0.076	0.061	0.146
Observations	3,037	2,967	3,037	3,037	3,024
School-grade FE	✓	✓	✓	✓	✓
Student controls	✓	✓	✓	✓	✓
Teacher controls	✓	✓	✓	✓	✓
Peer controls	✓	✓	✓	✓	✓

Notes. While Panel A use students’ own persistence in Grade 7 as the dependent variables, Panels B and C discuss variables related to students’ self-disciplined behaviors and education aspiration, respectively. In Panel A, the three items (Columns 1-3) and the average (Column 4) of Grade 7 persistence are standardized over estimation sample to have a zero mean and one standard deviation, and the MES refers to “mean effect size” calculated following Kling et al. (2007). ‘Peer persistence’ refers to the leave-one-out average of classmates’ persistence, while ‘Own persistence’ is students’ persistence in Grade 6. Both ‘Peer persistence’ and ‘Own persistence’ are standardized over the estimation sample to have a zero mean and one standard deviation. The student controls include age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, whether repeat grade in primary school, and non-cognitived measures in Grade 6. The teacher controls include the headteacher’s age, gender, teaching experience, and dummy variables indicating marital status, and having a college degree or above. Peer controls include the classroom proportion of female, migrant, and low-ability peers, and peer mothers with a college degree. Robust standard errors clustered at the school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2 Teacher Response

Teachers often play an important mediating factor between class environment and students' skill formation. [Golsteyn et al. \(2021\)](#) shows persistent peers are complemented by high-quality teachers in improving student achievement. However, it is unclear whether teachers adjust behaviors (e.g., become more responsible, provide more teaching inputs) in response to a classroom with more persistent students. Understanding how teachers might respond would shed more light on the complementary relationship between high-quality teachers and more persistent peers, as found in [Golsteyn et al. \(2021\)](#). I discuss this potential channel below.

To investigate, I draw on questions from various modules of the CEPS, including questionnaires of students, parents, and teachers. In the student questionnaire, CEPS asks students how they agree on the following statements, with a scale from 1 (strongly disagree) to 4 (strongly agree): “My headteacher always praises me” and “My headteacher always criticizes me”. I generate an indicator that equals one if students answer agree or strongly agree with the statement, and zero otherwise. For the parent questionnaire, CEPS asks parents two questions about their perception of “whether teachers are responsible/patient to their kids” with a scale from 1 (not at all) to 5 (very responsible/patient). I generate an indicator that equals one if parents think their kids' teachers are responsible/patient or are very responsible/patient, and zero otherwise.

As [Table 6](#) shows, students and parents have statistically significant perceptions of teachers being less criticizing (Column 2), and more responsible (Column 3) and patient (Column 4), suggesting teachers adjust behaviors in response to peer persistence in the classroom.

One concern with interpretations of the above results is they reflect students' and parents' perceptions of teacher behaviors, rather than the actual changes of teachers. To provide firmer evidence, I analyzed whether peer persistence affects teachers' time use on teaching preparation and grading at the level of subject teachers. CEPS surveys the three

subject teachers of each sampled classroom on their self-reported hours spent on teaching preparation, homework-and-exam grading last week. I take the log value of the reported hours and perform a subject-teacher level analysis that regresses teachers' time spend on the classroom-level persistence average.

The results are in Columns 5 and 6. When focusing on the time spent by each teacher last week, the results show that teachers spent more time in teaching preparation when there are more persistent students in the classroom. The time spent grading last week is also increased, albeit not statistically significant.²⁴

Table 6: Teacher Responses

	Student survey		Parents survey		Teacher survey	
	Headteacher praises me (1)	Headteacher criticizes me (2)	Teacher is responsible (3)	Teacher is patient (4)	Time spent in preparation (5)	Time spent in grading (6)
Peer persistence	0.021 (0.018)	-0.020* (0.011)	0.016* (0.009)	0.017* (0.009)	0.512** (0.240)	0.352 (0.255)
Own persistence	0.043*** (0.014)	-0.021*** (0.007)	-0.002 (0.006)	0.006 (0.007)	–	–
School-grade FE	✓	✓	✓	✓	✓	✓
Student controls	✓	✓	✓	✓	✓	✓
Teacher controls	✓	✓	✓	✓	✓	✓
Peer controls	✓	✓	✓	✓	–	–
Mean of dep. var.	0.544	0.125	0.928	0.896	2.332	2.361
R-squared	0.123	0.050	0.061	0.082	0.453	0.486
Observations	3,034	3,030	2,979	2,979	268	269

Notes. Columns 1 and 2 use students' perception of if their headteacher praises and criticizes them, while Columns 3 and 4 employ parents' perception of if their kid's teacher is responsible and patient. 'Peer persistence' refers to the leave-one-out average of classmates' persistence, while 'Own persistence' is students' persistence in Grade 6. Both 'Peer persistence' and 'Own persistence' are standardized over the estimation sample to have a zero mean and one standard deviation. Columns (5) and (6) analyze time spent in teaching preparation and grading at the subject-teacher level, where 'Peer persistence' refers to the classroom-level mean of students' persistence. The student controls include age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, whether repeat grade in primary school, and non-cognitive measures in Grade 6. The teacher controls include the headteacher's age, gender, teaching experience, and dummy variables indicating marital status, and having a college degree or above. Peer controls include the classroom proportion of female, migrant, and low-ability peers, and peer mothers with a college degree. Robust standard errors clustered at the school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

²⁴Alternatively, one might wonder if parents also play a role when having more persistent students in the classroom of their kids. In Appendix Table A8 Panel B, I tested if there are changes in parental investment in response to more persistent peers and found no effects.

5.3 Endogenous Friendship Formation

Carrell et al. (2013) informed the literature about the important role that endogenous peer group formation could play through which peer effects affect student achievement. When the focal student was assigned a larger number of peers with high persistence, endogenous friendship networks could develop, especially among students with homogeneous levels of persistence. People with similar characteristics (e.g., personality) are more likely to make friends with each other because of *homophily*.²⁵ Since persistent students tend to be those with better academic performance and more self-disciplined behaviors, the formation of friendships with persistent peers could lead to improvements in the focal student’s academic outcomes.

To empirically test the hypothesis, I draw on questions surveyed by CEPS on students’ up-to-five best friends and the behaviors of these nominated friends. CEPS first asks students to nominate up-to-five best friends, and asks students “how many of your best friends mentioned above fit in the following descriptions?” with a scale of 0 (none of them), 1 (one or two of them), and 2 (most of them): 1. doing well in academic performance; 2. studying hard; 3. aspiring to go to college; 4. skipping classes; 5. being criticized or punished for violating school rules; 6. always fighting with others; 7. smoking or drinking; 8. always going to net cafes or video arcades; 9. in a love relationship; 10. dropping out of school. Although the information about who were these best friends is not publicly available, I exploit these behavioral descriptions of best friends to study if there are changes in students’ friendship networks. Specifically, I create a dummy variable for each behavior description with a value of 1 indicating at least one of up-to-five best friends fitting into that behavior and a value of 0 indicating none of those nominated friends is in line with the description.

Panel A of Table 7 presents the results using the linear-in-mean model, showing having more persistent peers in the classrooms could: i) increase the likelihood of forming friendship

²⁵Homophily has been widely studied in friendship formation in both psychology (Selfhout et al., 2010; Wrzus et al., 2017) and economics literature (Jackson, 2010).

networks with students who have good grades or aspire to college (Columns 1-3); ii) decreases the likelihood of forming a friendship with disruptive peers who are fight or smoking and drinking (Columns 4-10). Note that these estimates significantly differ from zero even under a high/low mean of the dependent variable. For example, over 95% of the students reported they have a least one best friend who has a good grade. Still, having a 1 SD increase in peer persistence significantly increases the likelihood of making at least one best friend who has good grades by 0.015, which is a precisely estimated 1.58%-increase in the percentage compared to the dependent variable mean.

Although changes in friendship characteristics are found in Panel A, these findings are not necessarily interpreted as peer persistence affecting the formation of specific friendship networks. Having classmates with higher persistence mechanically leads to having more classmates with some specific behaviors (e.g., having a good grade, or less smoking/drinking), increasing the likelihood of the focal student forming friendships with these peers. This alternative interpretation could be especially true, given that over 90% students in the estimation sample report that they have at least one of up-to-five best friends from their class.

Ideally, to detect the friendship mechanism, we would have exact information on the friendship network, rather than a description of friendship characteristics. However, CEPS does not have friendship network data publicly available. To circumvent this, I use the idea of *homophily* to provide a fuller picture behind the findings in Panel A. If the friendship formation mechanism is true, then *homophily* could be the driving force behind these friendship characteristics changes. In other words, when having peers with higher persistence, we should expect high-persistence students to have more changes in their friendship characteristics, vis-á-vis medium- and low-persistence students.

Using specification (3), Panel B presents the heterogeneous effect of peer persistence on students with different baseline persistence. Results show a systematic pattern that high-persistent students have more changes in their friendship. Columns (1)-(10) show that

high-persistence students sort into friendship networks with “good” peers who have good grades, work hard, and want to attend college, while avoiding friendship with “bad” peers who perform truancy, disciplinary action, fight, smoking or drinking, and go to the net cafe. This pattern holds both for characteristics that detected changes under the linear-in-mean model and for other characteristics that count not be detected using the linear-in-mean model, highlighting the virtue of the heterogeneous effect model.

These results imply that friendship changes, especially among persistent students, are one underlying mechanism for understanding how peer persistence improves student academic achievement. When students with similar level of persistence are more likely to interact with each other (referred to as *homophily*), it gets easier for persistent students to improve achievement when other students in the classroom also demonstrate persistence in their learning. This could also indicate that persistent peers contribute to creating a more conducive learning environment. These findings align with the discussion on how the formation of peer groups, driven by endogenous factors, can impact the implications of optimal policy design on human capital formation, as highlighted in [Carrell et al. \(2013\)](#).

Table 7: Impacts of Peers' Persistence on Friendship Sorting

	"Good" peers network			"Bad" peers network						
	Good grade (1)	Hard working (2)	Aspiration to college (3)	Truancy (4)	Disciplinary action (5)	Fight (6)	Smoking or drinking (7)	Net cafe (8)	Love relationship (9)	Dropout (10)
Panel A. Linear-in-mean model										
Peer persistence	0.015** (0.007)	0.012 (0.007)	0.014** (0.006)	-0.003 (0.007)	-0.016 (0.011)	-0.021** (0.010)	-0.014* (0.007)	-0.011 (0.008)	-0.007 (0.009)	0.008 (0.006)
Own persistence	0.015*** (0.005)	0.019*** (0.006)	0.007* (0.004)	-0.010* (0.006)	-0.025*** (0.007)	-0.031*** (0.007)	-0.019*** (0.007)	-0.034*** (0.007)	-0.044*** (0.010)	-0.002 (0.004)
R-squared	0.062	0.057	0.051	0.071	0.082	0.088	0.063	0.117	0.074	0.043
Panel B. Heterogeneous effects										
Peer persistence*low persistence	0.016 (0.011)	0.004 (0.009)	0.014 (0.010)	0.002 (0.012)	-0.001 (0.016)	-0.013 (0.013)	-0.007 (0.012)	-0.006 (0.012)	-0.005 (0.014)	0.009 (0.007)
Peer persistence*medium persistence	0.012 (0.008)	0.007 (0.009)	0.001 (0.006)	0.007 (0.009)	-0.016 (0.016)	-0.013 (0.013)	0.001 (0.010)	0.002 (0.011)	-0.002 (0.014)	0.018** (0.008)
Peer persistence*high persistence	0.015** (0.007)	0.019** (0.009)	0.019** (0.007)	-0.012* (0.007)	-0.027** (0.011)	-0.032** (0.012)	-0.026*** (0.009)	-0.021** (0.009)	-0.012 (0.013)	0.003 (0.007)
R-squared	0.063	0.059	0.052	0.072	0.084	0.089	0.066	0.118	0.074	0.045
School-grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Student controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Teacher controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Peer controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean of dep. var.	0.952	0.946	0.964	0.041	0.076	0.080	0.038	0.068	0.108	0.021
Observations	2,969	2,969	2,969	2,969	2,969	2,969	2,969	2,969	2,969	2,969

Notes. The dependent variables in this table refer to, among the nominated up-to-five best friends, if the student has any friend has the following behaviors. Columns 1-3 and 4-10 classify behaviors related to "good" and "bad" peer friendship networks, respectively. See the main text for details of these behaviors. Panel A shows estimates obtained from the linear-in-mean model, while Panel B displays the results of the heterogeneous effect. 'Peer persistence' refers to the leave-one-out average of classmates' persistence, while 'Own persistence' is students' persistence in Grade 6. Both 'Peer persistence' and 'Own persistence' are standardized over the estimation sample to have a zero mean and one standard deviation. In Panel B, 'Peer persistence' is interacted with a dummy group of students' own persistence to assess the heterogeneous effect. The student controls include age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, whether repeat grade in primary school, and non-cognitive measures in Grade 6. The teacher controls include the headteacher's age, gender, teaching experience, and dummy variables indicating marital status, and having a college degree or above. Peer controls include the classroom proportion of female, migrant, and low-ability peer, and peer mothers with a college degree. Robust standard errors clustered at the school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Conclusion

I Exploit the student-classroom random assignment and a nationally representative student sample in middle schools in China to study the peer effects of persistence on student achievement and the underlying mechanisms. I investigate the impact of having more persistent peers in the classroom on students' academic achievement. I document the positive impacts of peers' persistence on student academic performance in baseline and follow-up waves. The impact on achievement is greater for students with medium and high levels of persistence.

Investigations of mechanisms reveal three sets of findings. When having more persistent students around: 1) students increase their own persistence, perseverance-related attitudes, and self-disciplined behaviors on academic attendance; 2) teachers become more responsible and patient, and spend more time on teaching preparation; 3) students form friendship networks with more “good” peers who perform well academically and less “bad” peers who have disruptive behaviors. I also document *homophily* that reconciles why having more persistent peers differentially raises academic performance of students with medium and high levels of persistence. Uncovering the peer effect of persistence and its mechanisms improve our understanding of optimal assignment policy design (Carrell et al., 2013) and mindset-based interventions (Alan et al., 2019).

References

- Alan, Sule, Teodora Boneva, and Seda Ertac**, “Ever failed, try again, succeed better: Results from a randomized educational intervention on grit,” *The Quarterly Journal of Economics*, 2019, *134* (3), 1121–1162.
- Almlund, Mathilde, Angela Lee Duckworth, James Heckman, and Tim Kautz**, “Personality psychology and economics,” in “Handbook of the Economics of Education,” Vol. 4, Elsevier, 2011, pp. 1–181.
- Altonji, Joseph G, Todd E Elder, and Christopher R Taber**, “Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools,” *Journal of political economy*, 2005, *113* (1), 151–184.
- Angrist, Joshua D**, “The perils of peer effects,” *Labour Economics*, 2014, *30*, 98–108.
- Bettinger, Eric, Sten Ludvigsen, Mari Rege, Ingeborg F Solli, and David Yeager**, “Increasing perseverance in math: Evidence from a field experiment in Norway,” *Journal of Economic Behavior & Organization*, 2018, *146*, 1–15.
- Bietenbeck, Jan**, “Peer Motivation and Educational Success,” 2021.
- Borghans, Lex, Angela Lee Duckworth, James J Heckman, and Bas Ter Weel**, “The economics and psychology of personality traits,” *Journal of human Resources*, 2008, *43* (4), 972–1059.
- Carman, Katherine Grace and Lei Zhang**, “Classroom peer effects and academic achievement: Evidence from a Chinese middle school,” *China Economic Review*, 2012, *23* (2), 223–237.
- Carrell, Scott E, Bruce I Sacerdote, and James E West**, “From natural variation to optimal policy? The importance of endogenous peer group formation,” *Econometrica*, 2013, *81* (3), 855–882.
- Chung, Bobby W and Jian Zou**, “Understanding spillover of peer parental education: Randomization evidence and mechanisms,” *Economic Inquiry*, 2023.
- Cools, Angela and Eleonora Patacchini**, “Peer Effects in Education 1,” *The Routledge Handbook of the Economics of Education*, 2021, pp. 253–275.
- Credé, Marcus, Michael C Tynan, and Peter D Harms**, “Much ado about grit: A meta-analytic synthesis of the grit literature.,” *Journal of Personality and social Psychology*, 2017, *113* (3), 492.
- Cunha, Flavio, James J Heckman, and Susanne M Schennach**, “Estimating the technology of cognitive and noncognitive skill formation,” *Econometrica*, 2010, *78* (3), 883–931.
- Damgaard, Mette Trier and Helena Skyt Nielsen**, “Nudging in education,” *Economics of Education Review*, 2018, *64*, 313–342.
- Duckworth, Angela and James J Gross**, “Self-control and grit: Related but separable determinants of success,” *Current directions in psychological science*, 2014, *23* (5), 319–325.

- Duckworth, Angela L, Christopher Peterson, Michael D Matthews, and Dennis R Kelly**, “Grit: perseverance and passion for long-term goals,” *Journal of personality and social psychology*, 2007, *92* (6), 1087.
- Eble, Alex and Feng Hu**, “How important are beliefs about gender differences in math ability? Transmission across generations and impacts on child outcomes,” *CDEP-CGEG Working Paper No*, 2019, *53*.
- **and** – , “Child beliefs, societal beliefs, and teacher-student identity match,” *Economics of Education Review*, 2020.
- Feng, Han and Jiayao Li**, “Head teachers, peer effects, and student achievement,” *China Economic Review*, 2016, *41*, 268–283.
- Golsteyn, Bart HH, Arjan Non, and Ulf Zölitz**, “The impact of peer personality on academic achievement,” *Journal of Political Economy*, 2021, *129* (4), 1052–1099.
- Gong, Jie, Yi Lu, and Hong Song**, “The Effect of Teacher Gender on Students’ Academic and Noncognitive Outcomes,” *Journal of Labor Economics*, 2018, *36* (3), 743–778.
- , – , **and** – , “Gender peer effects on students’ academic and noncognitive outcomes: Evidence and mechanisms,” *Journal of Human Resources*, 2019, pp. 0918–9736R2.
- Hagger, Martin S and Kyra Hamilton**, “Grit and self-discipline as predictors of effort and academic attainment,” *British Journal of Educational Psychology*, 2019, *89* (2), 324–342.
- He, Leshui and Stephen L Ross**, “Classroom peer effects and teachers: Evidence from quasi-random assignment in a Chinese middle school,” *Human Capital and Economic Opportunity Global Working Group Working Paper*, 2017, *14*, 2017.
- Heckman, James J and Yona Rubinstein**, “The importance of noncognitive skills: Lessons from the GED testing program,” *American Economic Review*, 2001, *91* (2), 145–149.
- , **Jora Stixrud, and Sergio Urzua**, “The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior,” *Journal of Labor economics*, 2006, *24* (3), 411–482.
- , **Tomás Jagelka, Tim Kautz et al.**, “Some Contributions of Economics to the Study of Personality,” Technical Report, NBER *Working Paper 26459* 2019.
- Hu, Feng**, “Do girl peers improve your academic performance?,” *Economics Letters*, 2015, *137*, 54–58.
- , “Migrant peers in the classroom: Is the academic performance of local students negatively affected?,” *Journal of Comparative Economics*, 2018, *46* (2), 582–597.
- Jackson, Matthew O**, *Social and economic networks*, Princeton university press, 2010.
- Kautz, Tim, James J Heckman, Ron Diris, Bas Ter Weel, and Lex Borghans**, “Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success,” Technical Report, National Bureau of Economic Research 2014.
- Kling, Jeffrey R, Jeffrey B Liebman, and Lawrence F Katz**, “Experimental analysis of neighborhood effects,” *Econometrica*, 2007, *75* (1), 83–119.

- Lavecchia, Adam M, Heidi Liu, and Philip Oreopoulos**, “Behavioral economics of education: Progress and possibilities,” in “Handbook of the Economics of Education,” Vol. 5, Elsevier, 2016, pp. 1–74.
- Lindqvist, Erik and Roine Vestman**, “The labor market returns to cognitive and noncognitive ability: Evidence from the Swedish enlistment,” *American Economic Journal: Applied Economics*, 2011, 3 (1), 101–28.
- Manski, Charles F**, “Identification of endogenous social effects: The reflection problem,” *The Review of Economic Studies*, 1993, 60 (3), 531–542.
- Martin, Andrew J**, “Motivation and engagement across the academic life span: A developmental construct validity study of elementary school, high school, and university/college students,” *Educational and psychological measurement*, 2009, 69 (5), 794–824.
- Neidell, Matthew and Jane Waldfogel**, “Cognitive and noncognitive peer effects in early education,” *The Review of Economics and Statistics*, 2010, 92 (3), 562–576.
- Oster, Emily**, “Unobservable selection and coefficient stability: Theory and evidence,” *Journal of Business & Economic Statistics*, 2019, 37 (2), 187–204.
- Sacerdote, Bruce**, “Peer effects in education: How might they work, how big are they and how much do we know thus far?,” in “Handbook of the Economics of Education,” Vol. 3, Elsevier, 2011, pp. 249–277.
- Selfhout, Maarten, William Burk, Susan Branje, Jaap Denissen, Marcel Van Aken, and Wim Meeus**, “Emerging late adolescent friendship networks and Big Five personality traits: A social network approach,” *Journal of personality*, 2010, 78 (2), 509–538.
- Shure, Nikki**, “Non-cognitive peer effects in secondary education,” *Labour Economics*, 2021, 73, 102074.
- Wang, Weidong and Pui-Wa Lei**, “Psychometric Report for Cognitive Ability Tests of CEPS Baseline (in Chinese),” Technical Report 2015. <https://ceps.ruc.edu.cn/assets/admin/org/ueditor/php/upload/20151222/14507142239451.pdf>.
- Wrzus, Cornelia, Julia Zimmermann, Marcus Mund, and Franz J Neyer**, “Friendships in young and middle adulthood: Normative patterns and personality differences,” *The psychology of friendship*, 2017, pp. 21–38.
- Xu, Di, Qing Zhang, and Xuehan Zhou**, “The Impact of Low-Ability Peers on Cognitive and Noncognitive Outcomes Random Assignment Evidence on the Effects and Operating Channels,” *Journal of Human Resources*, 2022, 57 (2), 555–596.

Appendix Figure and Table

Table A1: Balancing Test for Random Assignment

	Without school-grade FEs		With school-grade FEs	
	Coefficient (1)	SE (2)	Coefficient (3)	SE (4)
Student age	0.011	(0.019)	0.004	(0.019)
Female student	-0.003	(0.010)	0.000	(0.014)
Minority	-0.002	(0.010)	0.001	(0.005)
Agricultural Hukou	0.065*	(0.026)	-0.023	(0.016)
Non-local residence	-0.067***	(0.014)	-0.013	(0.013)
Sibling size	-0.003	(0.036)	-0.018	(0.030)
Attend kindergarten	-0.007	(0.010)	-0.008	(0.014)
Age attending primary school	0.094**	(0.040)	0.012	(0.028)
Repeat grade in primary school	0.007	(0.013)	-0.014	(0.010)
Parents' years of schooling	-0.487**	(0.184)	0.027	(0.094)
Persistence in Grade 6	0.153***	(0.019)	-0.037	(0.062)
Non-cognitive measures in Grade 6	0.106***	(0.025)	0.018	(0.036)

Notes. Each estimate is obtained from a separate regression which regresses one of students' pre-determined variables on the peers' persistence, using the estimation sample (N=3,051). Odd columns show the coefficient and even columns show the standard error (SE). Regressions in the Columns (3)-(4) include school-grade fixed effects. Robust standard errors clustered at the school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: Balancing Tests for Head Teacher Assignment

	class level average of persistence	
	(1)	(2)
Age	0.001 (0.017)	0.004 (0.025)
Female	0.103* (0.057)	0.135 (0.083)
Marriage status	-0.151* (0.081)	-0.194 (0.191)
Have a college degree	-0.136** (0.057)	-0.066 (0.124)
Teaching experience in years	0.001 (0.016)	-0.003 (0.021)
School-grade FE		✓
Observations	90	90

Note: Data are collapsed to classroom level for balancing analysis, where each observation represents one head teacher from one class. Each column shows a regression which regresses the average of classmate peers' persistence on a set of teacher characteristics. Column (2) includes school-grade fixed effects. Robust standard errors clustered at the school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Permutation Tests

Variable	P-value
Student age	0.487
Female student	0.489
Minority	0.288
Agricultural Hukou	0.471
Non-local residence	0.438
Sibling size	0.472
Attend kindergarten	0.501
Age attending primary school	0.510
Parents' years of schooling	0.489
Repeat grade in primary school	0.322
Non-cognitive measures in Grade 6	0.505
Persistence in Grade 6	0.510

Note: The table shows permutation tests using student's pre-determined variables and the associated p-value. The null hypothesis is students were randomly assigned to each classroom within the same school-grade unit. The distribution of the data meets exchangeability under the null hypothesis, which is also true for the distribution of re-sampled data. The permutation tests examine the distribution of re-sampled data in following three steps: 1) I calculate the actual classroom level mean of the predetermined variables of students; 2) I pool the students that are in the same school-by-grade block together, and then draw 10,000 classrooms (with a typical size of 39 students) from the student pool via re-samplings without replacement; 3) I compare the simulated class-level mean with the actual one for each predetermined variable, and calculate the p-value based on the probability of having simulated value lower than the actual one. Due to the re-sampling requirements, the sample is limited to students from a school-grade unit with at least 39 students (in 40 out of original 45 school-grade pairs in the estimation sample).

Table A4: Impacts of Peers' Persistence on Student Achievement by Subject

	Std. test score		
	Chinese (1)	Math (2)	English (3)
Panel A. Grade 7			
Peer persistence	0.031 (0.044)	0.129** (0.048)	0.127*** (0.044)
Own persistence	0.086*** (0.022)	0.081*** (0.022)	0.114*** (0.024)
R-squared	0.144	0.072	0.139
Panel B. Grade 8			
Peer persistence	0.110*** (0.037)	0.143** (0.057)	0.127*** (0.043)
Own persistence	0.094*** (0.021)	0.092*** (0.025)	0.111*** (0.022)
R-squared	0.158	0.078	0.141
School-grade FE	✓	✓	✓
Student controls	✓	✓	✓
Teacher controls	✓	✓	✓
Peer controls	✓	✓	✓
Observations	3,051	3,051	3,051

Notes. The dependent variables are subject test scores standardized by grade and school, to obtain a zero mean and one standard deviation. Panels A and B use test scores of students in Grade 7 and 8, respectively. 'Peer persistence' refers to the leave-one-out average of classmates' persistence, while 'Own persistence' is students' persistence in Grade 6. Both 'Peer persistence' and 'Own persistence' are standardized over estimation sample to have a zero mean and one standard deviation. The student controls include age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, whether repeat grade in primary school, and non-cognitive measures in Grade 6. The teacher controls include headteacher's age, gender, teaching experience, and dummy variables indicating marital status, and had college degree or above. Peer controls include the classroom proportion of female, migrant and low-ability peer, and peer mothers with a college degree. Robust standard errors clustered at school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Impacts of Peers' Persistence on Students' Non-Achievement Outcomes

	Self-assessment		Cognitive score		Mental stress	
	Grade 7 (1)	Grade 8 (2)	Grade 7 (3)	Grade 8 (4)	Grade 7 (5)	Grade 8 (6)
Panel A. Linear-in-mean model						
Peer persistence	0.092*** (0.029)	0.111*** (0.035)	0.039 (0.041)	0.104*** (0.027)	-0.053 (0.042)	0.016 (0.040)
Own persistence	0.067** (0.028)	0.026 (0.023)	0.019 (0.020)	0.032 (0.020)	-0.088*** (0.027)	-0.047** (0.022)
R-squared	0.187	0.202	0.274	0.328	0.092	0.076
Panel B. Heterogeneous effects						
Peer persistence*high persistence	0.040 (0.040)	0.088* (0.050)	0.046 (0.043)	0.104*** (0.037)	-0.012 (0.043)	0.048 (0.048)
Peer persistence*medium persistence	0.097** (0.044)	0.080* (0.045)	0.015 (0.052)	0.092*** (0.033)	-0.053 (0.049)	0.036 (0.046)
Peer persistence*medium persistence	0.098*** (0.030)	0.115*** (0.035)	0.042 (0.043)	0.105*** (0.027)	-0.063 (0.051)	-0.004 (0.044)
R-squared	0.200	0.215	0.275	0.329	0.101	0.083
School-grade FE	✓	✓	✓	✓	✓	✓
Student controls	✓	✓	✓	✓	✓	✓
Teacher controls	✓	✓	✓	✓	✓	✓
Peer controls	✓	✓	✓	✓	✓	✓
Observations	3,023	3,023	3,026	3,026	2,954	2,954

Notes. The dependent variables are students' self-assessment, cognitive scores, and mental stress in Grade 7 and 8. In Panel A, 'Peer persistence' is standardized over estimation sample to have a zero mean and one standard deviation. In Panel B, 'Peer persistence' is interacted with a dummy group of students' own persistence to assess the heterogeneous effect. The student controls include age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, whether repeat grade in primary school, and non-cognitive measures in Grade 6. The teacher controls include headteacher's age, gender, teaching experience, and dummy variables indicating marital status, and had college degree or above. Peer controls include the classroom proportion of female, migrant and low-ability peer, and peer mothers with a college degree. Robust standard errors clustered at school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Impacts of Peers' Persistence on Academic Outcomes: Bounding Exercises

	Std. test score				
	Baseline results	Self-assessment	Proportion of	Subject teacher sample	
	(1)	in Grade 6	accelerated peers	Baseline controls	Subject teacher controls
	(1)	(2)	(3)	(4)	(5)
Panel A. Grade 7					
Peer persistence	0.095*** (0.029)	0.099*** (0.028)	0.094*** (0.028)	0.080** (0.032)	0.065* (0.033)
Own persistence	0.094*** (0.013)	0.089*** (0.013)	0.093*** (0.013)	0.091*** (0.014)	0.089*** (0.014)
<i>Effect bounds and deltas</i>	[0.095, 0.250] $\delta = 6.1440$				
R-squared	0.103	0.194	0.103	0.103	0.104
Observations	9,153	9,135	9,153	8,538	8,538
Panel B. Grade 8					
Peer persistence	0.127*** (0.027)	0.130** (0.028)	0.123*** (0.026)	0.107*** (0.028)	0.100*** (0.031)
Own persistence	0.099*** (0.013)	0.094*** (0.012)	0.098*** (0.013)	0.096*** (0.014)	0.095*** (0.014)
<i>Effect bounds and deltas</i>	[0.127, 0.314] $\delta = 7.7271$				
R-squared	0.114	0.193	0.103	0.115	0.116
Observations	9,153	9,135	9,153	8,538	8,538
School-grade-subject FE	✓	✓	✓	✓	✓
Student controls	✓	✓	✓	✓	✓
Subject teacher controls	✓	✓	✓	✓	✓
Peer controls	✓	✓	✓	✓	✓

Note: The dependent variables are three subject exam scores standardized by grade and school, to obtain a zero mean and one standard deviation. Column 1 replicates the baseline results with an additional analysis of *effect bounds and deltas* following [Oster \(2019\)](#). Columns (2) and (3) add additional control to baseline specification, where column (2) adds self-assessment in Grade 6 and column (3) adds proportion of accelerated peers. Columns (4) and (5) use the sample with no missing values in all subject teacher controls. While Column (4) uses the baseline specification that uses headteacher controls, Column (5) uses the subject teacher controls. Panels A and B show results for achievement in Grade 7 and 8, respectively. ‘Peer persistence’ refers to the leave-one-out average of classmates’ persistence, while ‘Own persistence’ is students’ persistence in Grade 6. Both ‘Peer persistence’ and ‘Own persistence’ are standardized over estimation sample to have a zero mean and one standard deviation. The student controls include age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, whether repeat grade in primary school, and non-cognitive measures in Grade 6. The teacher controls include headteacher’s age, gender, teaching experience, and dummy variables indicating marital status, and had college degree or above. Peer controls include the classroom proportion of female, migrant and low-ability peer, and peer mothers with a college degree. Robust standard errors clustered at school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Falsification Tests: Peer Characteristics and Student Retrospective Measures

Panel A. Self-assessment in Grade 6			
	Chinese (1)	Math (2)	English (3)
Peer persistence	0.040 (0.049)	-0.019 (0.043)	0.027 (0.039)
Own persistence	0.075*** (0.021)	0.056*** (0.015)	0.125*** (0.023)
School-grade FE	✓	✓	✓
Mean of dep. var.	3.002	3.202	2.967
R-squared	0.106	0.099	0.151
Observations	3,040	3,039	3,021

Panel B. Persistence in Grade 6			
	School attendance (4)	Disliked homework (5)	Challenging homework (6)
Proportion female peers	0.484 (0.622)	-0.175 (0.422)	-0.249 (0.413)
Proportion migrant peers	-0.362* (0.212)	-0.135 (0.171)	-0.014 (0.125)
Proportion low-achieving peers	-0.474 (0.386)	-0.556 (0.369)	-0.708 (0.444)
Proportion college peer mothers	0.201 (0.289)	-0.060 (0.297)	-0.043 (0.286)
School-grade FE	✓	✓	✓
Mean of dep. var.	3.411	3.438	3.560
Observations	3,051	3,051	3,051

Notes. The dependent variables in Panels A and B are students' retrospective self-assessments and persistence measures in Grade 6, respectively. In Panel A, 'Peer persistence' refers to the leave-one-out average of classmates' persistence, while 'Own persistence' is students' persistence in Grade 6. Both 'Peer persistence' and 'Own persistence' are standardized over estimation sample to have a zero mean and one standard deviation. In Panel B, each estimate is obtained separately by regressing the retrospective persistence on one of the peers' characteristics, including proportion of female, migrant, and low-achieving peers, as well as proportion of college-educated peer mothers. All regressions include school-grade fixed effects. Robust standard errors clustered at school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Ruling out Alternative Mechanisms

Panel A. Students' time use				
	Study time on homework (1)	Study time on tutoring (2)	Time spent on watching TV (3)	Time spent on playing game (4)
Peer persistence	-0.029 (0.020)	-0.021 (0.021)	-0.003 (0.022)	-0.026 (0.027)
Own persistence	-0.006 (0.013)	0.002 (0.011)	-0.039*** (0.012)	-0.061*** (0.012)
Mean of dep. var.	1.103	0.396	0.602	0.459
R-squared	0.147	0.109	0.143	0.143
Observations	3,012	3,015	3,010	3,013
Panel B. Parental investment				
	Time spent with child per day (5)	“Did you guide your child on homework last week” (6)	Responsive parenting (7)	Demanding parenting (8)
Peer persistence	-0.009 (0.041)	-0.002 (0.015)	-0.000 (0.033)	-0.020 (0.031)
Own persistence	-0.027 (0.018)	0.019 (0.012)	0.019 (0.023)	0.042* (0.024)
Mean of dep. var.	1.115	0.697	–	–
R-squared	0.070	0.191	0.149	0.071
Observations	2,948	2,124	2,936	2,908

Notes. The dependent variables in Panel A and B are measurements representing parental investment on time and money and parenting style, respectively. The dependent variables in Panel C are two questions related to parents' networks. 'Peer persistence' refers to the leave-one-out average of classmates' persistence, while 'Own persistence' is students' persistence in Grade 6. Both 'Peer persistence' and 'Own persistence' are standardized over estimation sample to have a zero mean and one standard deviation. The student controls include age, gender, minority, hukou status, migrant status, sibling size, whether attended kindergarten, age attending primary school, whether repeat grade in primary school, and non-cognitive measures in Grade 6. The teacher controls include headteacher's age, gender, teaching experience, and dummy variables indicating marital status, and had college degree or above. Peer controls include the classroom proportion of female, migrant and low-ability peer, and peer mothers with a college degree. Robust standard errors clustered at school-grade level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.