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The Peer Effect of Persistence on Student Achievement

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Abstract

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Keywords: Peer effect; Personality trait; Human capital; Friendship formation
JEL Classification: I21, I24, J24

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1 Introduction

The critical 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 role of peer effects 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.[1]

Causal inference in estimating the impact of peer persistence 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. Such selection makes it infeasible to distinguish the impact of peers' persistence attributes from peers' academic abilities 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 variation in peer composition. The reflection problem refers to a student and her classmates in the same classroom who 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

[1]In the educational context, persistence reflects students' commitment to working hard and their resilience in overcoming academic obstacles, strongly correlated with the concept of *grit* (Duckworth et al., 2007). Persistent individuals 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).

that students in the same classroom receive in addition to the impact of peer persistence traits. To mitigate the effects of common shocks and obtain more precise estimates of the peer persistence effect, 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. The CEPS surveys detailed 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 academic year 2013-14, and then followed up when they moved to grade 8. Given the richness of the information in the CEPS, my study can observe and use changes in students and individuals around them in different dimensions and over time, which provides insights into the impact of peer persistence and potential mechanisms.

I find that peer persistence improves students' achievement in both baseline and follow-up waves. Students' achievement-related 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 achievement improvement 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 next assess the robustness of baseline findings. To obtain a clean interpretation of the effect, in addition to the random assignment of peers, one needs the assumption that variation in peers' persistence is unrelated to variation in peers' relevant unobserved characteristics (e.g., ability). In other words, one would need to validate that the baseline effect is driven by peers' persistence and not by other peers' characteristics. To assess the concern, I conduct a set of bounding exercises. I first show that baseline results remain robust after including additional ability controls: students' own self-assessment in grade 6, proportion of accelerated peers (a proxy indicating high-achieving peers), peer average of self-assessment, and subject teacher controls. I next perform an Oster (2019) test, which indicates that the selection on unobserved variables (e.g., peers' ability) must be at least six times larger than the selection on observed variables (e.g., peers' persistence) to reject the interpretation that the estimated baseline effect is due to peer persistence. These exercises help to mitigate the concern that the baseline results come from peer ability rather than peer persistence.[2]

I investigate three mechanisms that could underlie the impact of peer persistence: (i) students' own persistence and behavioral changes, (ii) teacher response, and (iii) endogenous friendship formation. When looking at student response, results show that having peers with higher persistence increases the focal student's persistence. Consistently, students' perseverance-related attitudes also improve – students agree that they can quickly adjust to mental stress and are more likely to aim for a college degree. Associated with the changes in persistence attitudes, students adopt more self-disciplined behaviors (as measured by decreases in tardiness and truancy), which improves the overall classroom environment. Results for teacher responses indicate that both students and parents are more likely to perceive teachers as more responsible and patient. In addition, teachers' self-reported time spent in teaching preparation increases. Investigations of students' friendship networks uncover that having more persistent peers in the classroom increases the likelihood that students make friends with "good" peers who perform well academically and avoid making friends with "bad" peers who misbehave, especially among students with similar levels of persistence.

The contribution of my study is twofold. First, it advances the understanding of the role non-cognitive skills play in skill formation.[3] The literature on the technology of skill formation highlights two key mechanisms: self-productivity and dynamic complementarity,

[2]I also validate the use of retrospective persistence measures when assessing the robustness of baseline results. See section 4.3 for discussion.

[3]The literature has integrated insights from developmental psychology into economics to underscore the significance of non-cognitive skills. See Heckman and Rubinstein (2001), Heckman et al. (2006), Borghans et al. (2008), Lindqvist and Vestman (2011), Almlund et al. (2011), Lavecchia et al. (2016), and Heckman et al. (2019), among others.

which implies that current skills 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 impact of peer personality by exploiting the random assignment of students to teaching sections in a college in the Netherlands. Their design involves random student assignments to small sections comprising up to 16 students, where students are required to spend considerable time studying together with meaningful social interactions. They find that students perform better in the presence of more persistent peers and that this impact endures over time, which is consistent with my findings.[4] My study exploits a similar assignment policy in the context of middle schools in China, where newly enrolled 7th-graders are randomly assigned to different classrooms within the grade in middle schools. Compared to Golsteyn et al. (2021), my study makes the following contributions: (i) it generalizes the existing research beyond developed countries and collegiate levels; (ii) in addition to traditional academic outcomes, it analyzes other achievement-related outcomes; (iii) it provides estimates with external validity by using a nationally-representative sample of middle school students; and (iv) it offers additional insights into the underlying mechanisms.[5]

My study also provides policy implications from two different perspectives. First, the insights into the mechanisms behind the peer persistence effect help open the black box of the recent mindset-based intervention literature (Damgaard and Nielsen, 2018; Bettinger

[4] A few other studies also examine the impact of peers' non-cognitive skills. Shure (2021) finds consistently positive impacts of conscientious peers on student achievement in the secondary setting in Belgium, with identification relying on a school fixed-effects framework. Neidell and Waldfogel (2010) document the negative impact of peer externalizing behaviors on students' academic outcomes, exploiting the preschool setting and plausible student-classroom random assignment within kindergartens in the United States. 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.

[5] Broadly speaking, this study also contributes to the research on peer effects in the economics of education literature (Sacerdote, 2011; Cools and Patacchini, 2021). Several other studies have used the same random assignment design to investigate the educational impact of various characteristics of peers, such as female peers (Hu, 2015; Gong et al., 2018), migrant peers (Hu, 2018), low-achieving peers (Xu et al., 2022), and college-educated peer parents (Chung and Zou, 2023). However, none of these papers examine the impact of peers' persistence.

et al., 2018; Alan et al., 2019). This literature mainly focuses on studying the direct effect without assessing spillovers. If there are spillover effects, the implications of mindset interventions become even more salient. The findings of how peer persistence affects the focal student's persistence could help researchers and policymakers to better understand and design mindset-based interventions. Second, my paper helps researchers rethink peer-based optimal policy design. Carrell et al. (2013) show how a failure to account for endogenous friendship formation could lead to inefficient design in the peer-based optimal policy. My study provides empirical evidence for 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

China's K-12 education system encompasses six years of primary school (grades 1 to 6), followed by three years each of junior high (grades 7 to 9) and senior high school (grades 10 to 12). Initiated in 1986, the Compulsory Education Law (CEL) mandates nine years of compulsory schooling, spanning both primary and junior high stages.[6] Although structurally akin to their international counterparts, Chinese middle schools could exhibit some cultural and pedagogical differences relevant to understanding the educational impact of peer persistence. The competitive educational climate, driven by the centralized college admissions system, encourages students to compete academically. As a result, students who exhibit persistence often see benefits in their academic achievement. Due to the collectivist nature of classrooms, students displaying persistence are also highly valued by their peers, enhancing the classroom atmosphere and encouraging social interactions. In

[6]See 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.

addition, teachers acknowledge the benefits of having persistent students, noting their higher test scores and reduced disruptions.[7] Believing teaching pedagogy is an important input affecting student achievement, teachers are also more likely to respond to a classroom with more persistent peers by adjusting their teaching investments.

In 2006, the Compulsory Education Law underwent revisions that included 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 additional charges. In addition, the 2006 CEL explicitly prohibited tracking in primary and junior high schools to ensure equal and equitable opportunities for all students.[8]

In practice, while not all junior high schools have adopted a random assignment policy since 2006, such assignments have become increasingly popular. The assignment process occurs at the beginning of junior high school (grade 7), where newly enrolled students are assigned to classrooms through a random selection process. While the specific random assignment strategies may vary among schools, I outline two common methods: i) purely random assignment and ii) the "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 "balanced assignment", involves quasi-random assignments that would balance the test scores of incoming students across classrooms.[9] While CEPS did not survey assignment details, I follow the literature to identify school

[7] As Figure A1 indicates, surveyed teachers (N = 1,243) believe the most relevant factor for students' academic achievement is students' study attitudes, followed by students' study methods and teachers' pedagogy.

[8] See 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`.

[9] The "balanced assignment" approach is commonly employed to identify quasi-random variation 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)). An example of a "balanced assignment" is the following scenario with five classes and 200 students in grade 7. Based on their baseline test scores, the school ranks these 200 students 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 have been assigned to a classroom.

samples that implement the random-assignment policy.[10]

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 Renmin University of China, CEPS is a large-scale longitudinal survey that is nationally representative. CEPS employs the PPS (probability proportional to size)-based stratified and multistage sampling design to collect a nationally representative sample. The sampling process first selects county-level divisions (henceforth, county) and then selects middle schools within the counties.[11] 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 CEPS.[12]

In the first wave, CEPS surveyed 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, grade 7 students were followed when they moved to grade 8, while grade 9 students (a pilot sample) were not. To date, CEPS has only released the first two waves. Since I use retrospective measures of persistence, I did not use 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

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

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

[12] See details of CEPS at http://ceps.ruc.edu.cn/English/Overview/Overview.htm.

students move to 8th grade. This process leads to 49 schools remaining, which account for 43.8% (49 out of 112) of the school sample.

After selecting school samples, I exclude students who switch classrooms when they moved to grade 8, and 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 four schools with only one grade 7 class. In the end, I obtain a final estimation sample of 3,051 students across 90 classrooms in 45 schools, along with their demographic variables and outcomes in both waves, as well as information on their parents and teachers.[13]

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

Persistence.— Persistence is a personality trait related to Conscientiousness in the Big Five personality model. Persistence reflects the extent to which students work hard and their ability to persevere when facing challenges and setbacks, which is strongly correlated with *grit* (Duckworth et al., 2007). 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. I follow the Big Five model, a canonical model in Psychology, to classify these seven questions into different personality categories.[14] The first three measure 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

[13]Table A1 provides a waterfall table that details the changes in the sample size of schools, classes, and students during the sample selection procedure.

[14]The CEPS collects 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 in identifying the relationship between these seven items and the Big Five personality factors — Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

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 standardize each item over the estimation sample to obtain a mean of zero and a standard deviation (henceforth, SD) of one. I then take the average of the three standardized items to construct a persistence index and normalize the averaged index again.[15]

The persistence scale in CEPS is similar to that used in Golsteyn et al. (2021), which originates from the Student Motivation Scale developed by psychologist Martin (2009).[16] The similarity between the two persistence measurements provides *criterion validity* to the CEPS's persistence scale. 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.[17]

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. These test scores are obtained directly from the school administrations by the CEPS. In wave one, the CEPS standardizes the test scores to have a mean of 70 and a standard deviation of 10. I then standardize the test scores by school-grade-subject level to have a zero mean and

[15] The other four questions relate to Extraversion and Openness in the Big Five model. The same scale (from 1 to 4) is applied to 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 things". While the first two items relate to Extraversion, the last two relate to Openness. Since these 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 *noncognitive measures* in grade 6. Similar to persistence, I standardize items first, then average them, and finally normalize the averaged index over the entire estimation sample.

[16] In 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."

[17] A remaining issue relates to the use of retrospective measures. For example, students might rate their 6th-grade persistence using the reference of the current classroom environment in grade 7, and students with different abilities could recall their 6th-grade persistence differently. I discuss and address these concerns in section 4.3.

unit standard deviation. 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, for ease of interpretation, I scale the raw test score with the total score for each student first and then normalize the scaled scores over the estimation sample.

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

For self-assessment on each subject, the CEPS asks students "Whether the following courses were difficult for you in grade 7?" for the three subjects, using a scale from 1 (very difficult) to 4 (not difficult at all). I standardize each item, calculate the average of the three standardized items, and then normalize the average again. The estimated impacts on self-assessment of each subject can complement the results found on students' achievement. For example, if peer persistence increases students' test scores, we would expect positive effects when examining the impact on the self-assessment.

The cognitive score is obtained from the cognitive assessment test developed and implemented by the CEPS. The cognitive score is assessed for all surveyed students, allowing for a universal comparison. The cognitive test assesses students' general ability, rather than specific knowledge learned.[18] I directly use the standardized cognitive scores provided by the CEPS, which are generated using a three-parameter logistic (3PL) model. The investigation of cognitive scores is also informative, as the assessment captures students' ability formation. Therefore, we would also expect increases in students' cognitive scores when there are improvements in student achievement.

To examine students' mental stress, I use four questions in both waves to measure mental stress, following Gong et al. (2019). The CEPS asks students, "Have you had the following feelings 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.[19] Again, I normalize

[18]The cognitive test assesses students' cognition via three dimensions: verbal, graphical and spatial, and computational and logical. The construction of the cognitive assessment follows that of the Taiwan Education Panel Survey (Wang and Lei, 2015).

[19]In wave two, CEPS asks students "blue" with a slightly different description — "blue and thus cannot

each item, average the four normalized items, and normalize the averaged index over the estimation sample. 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 student controls. The control variables include age, gender, ethnicity, rural status, local residency status, number of siblings, attendance of kindergarten, age of attending primary school, parent's years of schooling, and persistence and noncognitive measures in grade 6. These predetermined variables are used to perform balancing tests and are included in the estimations to improve estimation precision. Table 1 presents the statistical description.

focus".

Table 1: Summary Statistics

	All	
	Mean	SD
A. Outcome variables		
Test score in grade 7	70.601	8.252
Test score in grade 8	70.582	8.475
B. Variables of interests:		
Peer 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
Persistence in grade 6	3.470	0.624
Non-cognitive measures in grade 6	3.271	0.573
Observations[#]	3,051	

Notes. The table displays the means and standard deviations (SD) of the estimation sample. The table presents the raw values of test scores, persistence and non-cognitive measures in grade 6, and averages of peers' persistence, whereas the regression analysis utilizes the standardized values of these variables.
The number of observations 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 variation (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:

$$\overline{\text{PeerPersistence}}_{\text{-i,j,k}} = \beta_0 + \beta_1 \text{X}_{\text{i,j,k}} + \delta_{\text{k}} + \epsilon_{\text{i,j,k}} \tag{1}$$

where $\overline{\text{PeerPersistence}}_{\text{-i,j,k}}$ is the leave-one-out average of peer persistence in class j within school-grade k. Persistence is measured in grade 7 regarding students' retrospective persistence attitudes in grade 6.[20] $X_{i,j,k}$ is the set of students' predetermined variables, as outlined in Table 1 Panel C. δ_k is the school-grade fixed effects.[21] ϵ_i is the error term, which is clustered at the school-by-grade 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 attends (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

[20] When later discussing mechanisms (i.e., section 5.1), the analysis uses students' persistence measured in grade 8, which reflects their retrospective persistence attitudes in grade 7.

[21] Since only 7th-grade students are included in this study, the school-grade fixed effects are identical to the school fixed effects. However, to avoid any confusion, I refer to "school-by-grade" as 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:

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

where $\mathrm{Y}_{i,s,j,k}$ is the test score of student i in subject s in class j and school-by-grade 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 $\delta_{\mathrm{s,k}}$. 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 $\mathrm{T_{i,j,k}}$ and peer controls $\mathrm{P_{i,j,k}}$. The teacher controls include headteachers' age, gender, teaching experience, and dummy variables indicating marital status, and having a college degree or above.[22] Peer controls include the leave-one-out average of female, migrant, and low-ability peers, and peer mothers with a college degree.[23] Standard errors are clustered at the school-by-grade 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.

While the specification is widely adopted in the peer effect literature, I would like to note

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

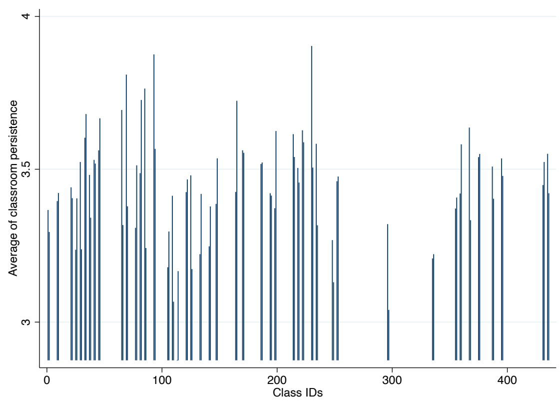
[23] See studies that show the impact of female peers (Hu, 2015; Gong et al., 2019), migrant peers (Hu, 2018), low-ability peers (Xu et al., 2022), peer maternal education (Chung and Zou, 2023) on student outcomes, exploiting the same data and identification strategy.

that it is important to consider whether the current design accurately identifies the peer persistence effect. Random assignment, in this case, also generates other peer variations (e.g., peer controls) that could potentially impact student achievement. Therefore, it is crucial to isolate the variation in a specific trait (e.g., peer persistence) to obtain a clear interpretation. However, the current design does not fully address this issue, as it is only flexible to control for observable peer characteristics when estimating the effect, rather than holding all else equal to identify the causal effects of having more persistent peers. This drawback raises concerns about whether the estimated effect indeed stems from the persistence of peers or from other characteristics of the peers. Although efforts have been made to address this concern through testings, such as bounding exercises in section 4.3, it is still important to exercise caution when interpreting the estimated peer persistence effect.

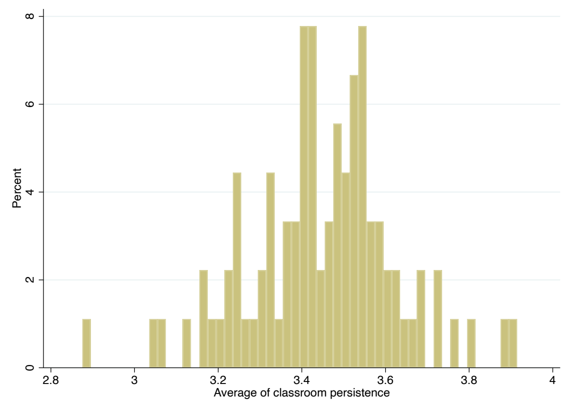
3.3 Tests for Random Assignment

Before performing the balancing test, I check if there is sufficient variation in the average class-level persistence, both unconditional and conditional on each school-grade cell. Figure 1 shows the unconditional averages of class-level persistence across different classes (Figure 1a) and the associated histogram (Figure 1b). The figures confirm that there is sufficient variation in the means of class-level persistence in general. Consistent with the research design, Figure 2 displays scatter dots of persistence averages across the two classrooms within each school-grade block (Figure 2a) and the associated histogram of the differences within each school-grade (Figure 2b). If the classroom assignments fail to generate enough differences in the persistence averages across classrooms, we would expect to see most of the dots in Figure 2a close to the red 45-degree line. However, Figure 2a reveals large differences in persistence averages between the two classrooms, resulting in 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 lie on the 45-degree line, indicating sufficient identifying variation.[24]

Figure 1: Variation of Class-Level Persistence



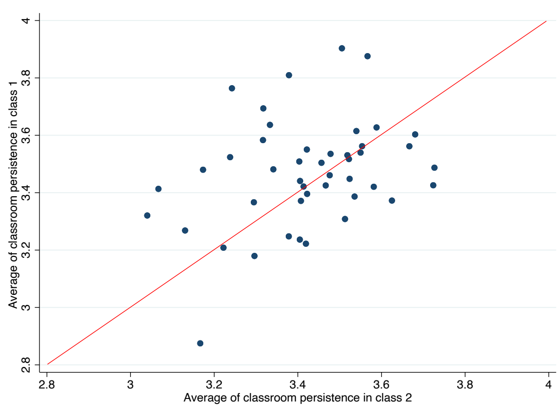
(a) Raw distribution



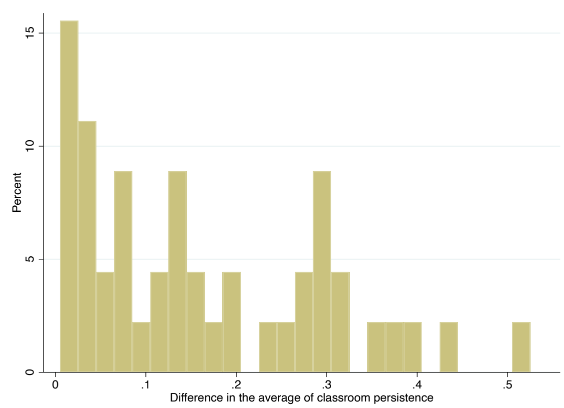
(b) Histogram of class-level persistence

Note. Figure 1a shows the raw distribution of the averages of class-level persistence. Figure 1b plots the histogram of the average class-level persistence (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



(a) Scatter plot of within-grade variation



(b) Histogram of between-class difference

Note. Figure 2a plots the averages 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 class pairs having values that differ from zero.

[24] Figure A2 provides the distribution of individual-level variation in peers' persistence, both unconditional and conditional on the school-grade fixed effects. The demeaned distribution (i.e., conditional on the school-grade fixed effects) plots the variation used in the analysis, which indicates sufficient variation on the leave-one-out average of peers' persistence.

Though other researchers in the literature have validated the employed identification strategy, I formally assess the randomness of the within-grade peer persistence variation by conducting 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 from lower socioeconomic backgrounds (e.g., having an agricultural *hukou* and less educated parents), more likely to be local residents, and having higher persistence and noncognitive measures in grade 6. Without adding school-grade fixed effects, student sorting could occur across schools or classrooms, making the results hard to interpret. 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 are correlated with her peers' persistence average, indicating a good balancing for the within-grade peer persistence variation. 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).[25] I also conduct F-statistics tests to investigate the joint significance of student controls on predicting peers' persistence. The joint tests indicate that student controls predict significantly the peer persistence in the model without school-grade fixed effects (p-value as 0.0016), and adding school-grade fixed effects reduces the predictive power largely (p-value as 0.0951).[26]

[25]Alternatively, one can perform balancing tests that regress one predetermined variable of students on their peers' persistence means, without and with school-grade fixed effects. The results are in Table A2, which show a similar balancing pattern and endorse the identification. In addition, one can conduct balancing tests at the classroom level, which regress 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 Table A3.

[26]The marginal significance (p-value as 0.0951) is likely caused by the use of students' retrospective measures rather than a violation in the random assignment. Note that the focal student's retrospective measures could be correlated with those of her peers when persistence attitudes are measured in grade 7, which introduces a correlative relationship between students' retrospective measures and the constructed peer persistence. To test this possibility, I conduct another joint test of student controls, but excluding retrospective measures. The results show that, while students' non-retrospective predetermined variables significantly predict peer persistence in the absence of school-grade fixed effects (p-value as 0.0072), these variables do not have significant predictive power when adding school-grade fixed effects (p-value as 0.4286). The results support that the marginal significance was a result of including retrospective measures, rather than a violation in the randomness. Regarding the potential concerns of using retrospective measures, I discuss and address them in section 4.3.

Table 2: Balancing Tests for Random Assignment

	Peer persistence	
	(1)	(2)
Student age	-0.003	0.004
	(0.009)	(0.005)
Female student	-0.003	0.001
	(0.008)	(0.005)
Minority	-0.004	0.001
	(0.029)	(0.010)
Agricultural *hukou*	0.049**	-0.010
	(0.019)	(0.008)
Non-local residence	-0.093***	-0.004
	(0.024)	(0.008)
Sibling size	-0.014	-0.002
	(0.013)	(0.006)
Attend kindergarten	-0.010	-0.008
	(0.017)	(0.011)
Age attending primary school	0.016*	0.001
	(0.009)	(0.003)
Repeat grade in primary school	0.006	-0.021
	(0.032)	(0.012)
Parents' years of schooling	-0.009**	-0.000
	(0.003)	(0.001)
Persistence in grade 6	0.022***	-0.005
	(0.008)	(0.005)
Non-cognitive measures in grade 6	0.014**	0.004
	(0.006)	(0.003)
P-value of joint significance:		
Student controls	0.0016	0.0951
Student controls (excluding retrospective measures)	0.0072	0.4286
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. Joint test p-values of student controls, with and without retrospective measures, are provided. 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 (i.e., self-assessment, cognitive scores, and mental stress). Following the baseline results, I explore heterogeneous effects and address potential concerns with robustness checks.

4.1 Impacts on Academic Achievement

Table 3 shows the impact of peer persistence on students' outcomes. Panels A and B examine students' outcomes in grades 7 and 8, respectively. While columns (1) to (4) show the impact of peers' persistence on student achievement, columns (5) to (7) examine the impact on students' non-achievement outcomes.

Results in Panel A column (1) indicate that having classmates with higher persistence improves student achievement in grade 7. The estimates imply that a one standard deviation increase in peers' persistence leads to a 0.095 standard deviation increase in standardized test scores at the baseline. When looking at grade 8, results in Panel B also find a positive impact of having more persistent peers on student achievement. Estimates in column (1) indicate that a one standard deviation increase in peers' persistence leads to a 0.127 standard deviation increase in test scores at the follow-up wave, finding a slightly larger magnitude than the one at the baseline. The results imply a lasting impact that increases from additional exposure to persistent peers. The effect is also consistent with the channel of friendship networks discussed later, which takes time to form and develop.

To provide insights into the underlying drivers, columns (2) to (4) look at the impact on test scores by subject. Panel A shows that Math and English underlie the overall effect on student achievement at the baseline. Panel B indicates additional improvements in Chinese test scores, which become the driving forces that lead to increased academic performance in the follow-up wave.

I elaborate on some implications of the effect size found in this study. First, one can assess how the impact on test scores could relate to students' crucial downstream outcomes, such as future earnings. Using a large-scale college student survey, Bai et al. (2021) estimate that a one-standard-deviation increase in the college entrance exam score is associated with 2.6–2.9% higher first-job wages. Drawing upon their estimates, one can infer that a one standard deviation increase in peer persistence is related to a 0.33%–0.37% (calculated as 0.127 multiplied by 2.6–2.9%) wages premium for the first job. Second, we can compare the effect size of this study to those from other inputs of the education production function. For example, the effect size of peer persistence (0.095 standard deviations for 7th-graders and 0.127 standard deviations for 8th-graders) is similar to those identified in teacher value-added (0.14 standard deviations in math and 0.1 standard deviations in English, as found in Chetty et al. (2014)), and slightly surpasses those reported in the ordinal ranking literature (0.08 standard deviations, as per Murphy and Weinhardt (2020)).

In addition to student achievement, I check whether there are impacts 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 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 columns (5) to (7). The results reveal that students have higher self-assessments when more persistent peers are around. Students with more persistent peers also have higher cognitive scores at baseline, though the difference is not significantly different from zero (Panel A column 6). However, the improvement in cognitive assessment becomes significantly different from zero when students move to grade 8 (Panel B column 6). In the end, column (7) shows peers' persistence has no impact 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 Students Outcomes

	Achievement				Non-achievement outcomes		
	Test score (1)	Chinese (2)	Math (3)	English (4)	Self-assessment (5)	Cognitive score (6)	Mental stress (7)
Panel A. Grade 7							
Peer persistence	0.095***	0.031	0.129**	0.127***	0.092***	0.039	-0.053
	(0.029)	(0.044)	(0.048)	(0.044)	(0.029)	(0.041)	(0.042)
Own persistence	0.094***	0.086***	0.081***	0.114***	0.067**	0.019	-0.088***
	(0.013)	(0.022)	(0.022)	(0.024)	(0.028)	(0.020)	(0.027)
R-squared	0.103	0.144	0.072	0.139	0.187	0.274	0.092
Panel B. Grade 8							
Peer persistence	0.127***	0.110***	0.143**	0.127***	0.111***	0.104***	0.016
	(0.027)	(0.037)	(0.057)	(0.043)	(0.035)	(0.027)	(0.040)
Own persistence	0.099***	0.094***	0.092***	0.111***	0.026	0.032	-0.047**
	(0.013)	(0.021)	(0.025)	(0.022)	(0.023)	(0.020)	(0.022)
R-squared	0.114	0.158	0.078	0.141	0.202	0.328	0.076
School-grade(-subject) FE	✓	✓	✓	✓	✓	✓	✓
Student controls	✓	✓	✓	✓	✓	✓	✓
Teacher controls	✓	✓	✓	✓	✓	✓	✓
Peer controls	✓	✓	✓	✓	✓	✓	✓
Observations	9,153	3,051	3,051	3,051	3,023	3,026	2,954

Notes. The dependent variables are students' standardized test scores (in the pooled sample, and separated into Chinese, Math, and English), self-assessment, standardized cognitive scores, and mental stress in grades 7 (Panel A) and 8 (Panel B). 'Peer persistence' is 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. Column (1) includes school-grade-subject fixed effects, while the rest use school-grade fixed effects. Robust standard errors clustered at the school-grade level are in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

4.2 Heterogeneous Effects

While the linear-in-mean framework captures the average treatment effect behind the exogenous variation of peer persistence, heterogeneity analyses can uncover 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. Then, I calculate the interaction terms between peer persistence and the three indicators. By replacing the peer persistence and students' own persistence in equation (2) with the three interaction terms and the three indicators, I obtain the following specification:

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

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

Table 4 Panel A shows the heterogeneous effect of peer persistence on students' academic outcomes. In grade 7, medium- and high-persistent students benefit more from persistent peers in achieving better academic performance than low-persistent students. In the follow-up academic year, while medium- and high-persistence students continue to benefit from having higher-persistence peers, students with low persistence also begin to benefit (column 2). The achievement gains of these low-persistence students partially explain the overall improvement found in the baseline results when students are in grade 8.

Columns (3) to (8) in Panel A examine the heterogeneous effect of peer persistence on students' non-achievement outcomes. The heterogeneous effect on self-assessment exhibits 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 3-4). The effect on cognitive scores is not significantly different from zero in the baseline and then increases significantly in the follow-up wave (columns 5-6). Columns (7)-(8) 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 levels of persistence.

Similarly, we can also examine how the impact of peer persistence might vary based on the focal student's self-assessment in grade 6, another measure related to students' initial skills. As Table 4 Panel B indicates, students with high baseline self-assessment benefit more from having more persistent peers in improving their academic achievement, self-assessment, and cognitive score. Meanwhile, no heterogeneous effects are found on students' mental stress.

4.3 Addressing Potential Concerns

I now address two concerns regarding the benchmark estimations: the use of retrospective persistence measures and the threat of peers' unobservable characteristics (e.g., lack of baseline academic ability as a control).

One possible concern regarding retrospective persistence is that students may rate their 6th-grade persistence in the context of the new classroom environment, when surveyed in grade 7. If so, retrospective persistence measures would be a function of the current environment, leading to a reflection problem when estimating the peer persistence effect. To address this possibility, I directly test whether there is a relationship between each retrospective persistence item and current peers' characteristics. Each estimate in Panel A of Table A4 is obtained from a separate regression that regresses one of the 6th-grade persistence

Table 4: Heterogeneous Effects of Peers' Persistence on Students' Outcomes

	Achievement		Non-achievement outcomes					
	Test score		Self-assessment		Cognitive score		Mental stress	
	Grade 7	Grade 8	Grade 7	Grade 8	Grade 7	Grade 8	Grade 7	Grade 8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. By persistence in grade 6								
Peer persistence*low persistence	0.052	0.100***	0.040	0.088*	0.046	0.104***	-0.012	0.048
	(0.037)	(0.035)	(0.040)	(0.050)	(0.043)	(0.037)	(0.043)	(0.048)
Peer persistence*medium persistence	0.082**	0.107***	0.097**	0.080*	0.015	0.092***	-0.053	0.036
	(0.034)	(0.032)	(0.044)	(0.045)	(0.052)	(0.033)	(0.049)	(0.046)
Peer persistence*high persistence	0.120***	0.145***	0.098***	0.115***	0.042	0.105***	-0.063	-0.004
	(0.028)	(0.028)	(0.030)	(0.035)	(0.043)	(0.027)	(0.051)	(0.044)
R-squared	0.107	0.118	0.200	0.215	0.275	0.329	0.101	0.083
Observations	9,153	9,153	3,023	3,023	3,026	3,026	2,954	2,954
Panel B. By self-assessment in grade 6								
Peer persistence*low self-assessment	0.078**	0.111***	-0.005	0.063*	0.026	0.103***	-0.019	0.007
	(0.035)	(0.032)	(0.023)	(0.036)	(0.047)	(0.034)	(0.047)	(0.047)
Peer persistence*medium self-assessment	0.048*	0.083***	0.014	0.075*	0.011	0.059**	-0.047	0.053
	(0.028)	(0.028)	(0.015)	(0.044)	(0.043)	(0.028)	(0.047)	(0.044)
Peer persistence*high self-assessment	0.093***	0.108***	0.021	0.083*	0.055	0.128***	-0.046	0.048
	(0.035)	(0.033)	(0.023)	(0.048)	(0.055)	(0.031)	(0.050)	(0.059)
R-squared	0.173	0.187	0.832	0.340	0.288	0.351	0.120	0.098
Observations	9,108	9,108	3,023	3,023	3,011	3,011	2,940	2,940
School-grade(-subject) FE	✓	✓	✓	✓	✓	✓	✓	✓
Student controls	✓	✓	✓	✓	✓	✓	✓	✓
Teacher controls	✓	✓	✓	✓	✓	✓	✓	✓
Peer controls	✓	✓	✓	✓	✓	✓	✓	✓

Notes. The dependent variables are students' standardized test scores, self-assessment, cognitive scores, and mental stress in grades 7 and 8. 'Peer persistence' is standardized over the estimation sample to have a zero mean and one standard deviation. 'Peer persistence' interacts with a dummy group of students' own persistence (Panel A) or self-assessment (Panel B) 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 peers, and peer mothers with a college degree. Columns (1) and (2) include school-grade-subject fixed effects, while the rest use school-grade fixed effects. Robust standard errors clustered at the school-grade level are in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

items on each of the peer characteristics – the leave-one-out average of female peers, migrant peers, low-achieving peers, college-educated peer mothers, and peers' persistence. Although the proportion of migrant peers and the retrospective persistence on school attendance is significantly correlated at the 10% level, there is no systematic relationship between peer characteristics and retrospective persistence items across the rest of all regressions. The results alleviate the concern that students use their current set of peers as the reference group when reporting their levels of recalled persistence.

When using retrospective persistence in the estimation, another concern relates to measurement errors. 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 recall their actual persistence better, and these characteristics could also affect academic outcomes. If this concern is valid, the constructed average of peer persistence would combine peers' baseline persistence and other skills, thereby 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, Table A2 shows that, 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 address the concern about measurement errors, I conduct a falsification test that regresses the focal student's retrospective self-assessment 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), these skills would also likely be correlated with retrospective self-assessment in grade 6. However, Panel B of Table A4 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 concern relates to how failure to control unobservable variables, such as the abilities of incoming students, might bias baseline estimates and affect our interpretation of the estimated effect. A shortcoming of the CEPS is its lack of students' baseline test scores. The absence of prior test scores does not break random assignment, but it raises concerns about estimation biases. For instance, when higher persistence is proxying higher prior test scores, the absence of baseline academic abilities could lead to an upward bias when estimating the impact of peer persistence on student achievement. In addition to baseline test scores, there could be other unobservable variables (e.g., socio-economic status, family values, or other non-cognitive skills) that cannot be completely controlled for, raising the concern on our interpretation of the estimated effect — whether the effect is driven by peers' persistence or by other peers' characteristics that could affect performance. Although my study controls for almost all students' predetermined characteristics that are available in CEPS, formally, I assess these concerns by conducting bounding exercises below.

I first examine the coefficient stability by including additional ability-related controls. Column (1) of Table A5 replicates the baseline estimation. In columns (2) to (4), the regressions separately add additional controls, including the proxy for the focal student's baseline academic ability (self-assessment in grade 6) and two controls for peers' ability (leave-one-out average of accelerated peers who ever skipped a grade in the primary school and leave-one-out average of 6th-grade self-assessment). Additionally, the specification in column (5) includes all three controls added in columns (2) to (4). The estimates are robust across specifications with these additional ability controls.[27]

However, as Oster (2019) discusses, the stability of the coefficient could be due to the additional controls being less important in explaining students' achievement, rather than indicating the bias is small. Inspired by Altonji et al. (2005), Oster (2019) proposes a consistent estimator to improve the assessment by incorporating movements in R-squared. The underlying intuition is straightforward: only considering changes in the 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}).[28]

Based on the assumptions above, Table A5 assesses the coefficient stability. 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

[27] In columns (6) and (7), I also assess the importance of subject teacher controls. The exercise uses a sample with no missing values in all subject teacher controls. Column (6) follows the same specification as the baseline one, and column (7) 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 could be partially driven by 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.

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

R^2 from the fully controlled specification in column 1), as suggested by Oster (2019). The obtained R_{max} is 0.134 and 0.148 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 six 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 seven times larger than the selection on observed variables to fully explain the estimated effect on achievement in grade 8 (δ=7.7271), and the effect bound never includes zero (between 0.127 and 0.314). Taken together, these results mitigate our concern that the baseline estimated effect comes from peer ability rather than peer persistence.

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' responses, and endogenous friendship formation.

5.1 Students' Own Persistence and Behaviors

Alan et al. (2019) show 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. With persistence being 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 7th-grade persistence, measured by the same persistence scale.[29] 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 then 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 challenging homework, as shown in columns (1)-(3). On average, a one SD in peer persistence increases students' persistence by 0.111 SD (column 4). I also follow Kling et al. (2007) to estimate the mean effect sizes, which provide an aggregated effect and reduce the chance of false positives.[30] The result is robust to adjusting for multiple hypothesis testing, 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 in the face of 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

[29]Specifically, CEPS surveys students, asking them "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). The survey includes the same three questions as the baseline survey, and an additional question: "I would persist in my interests and hobbies."

[30]While both the simple averaged index and mean-effect-size (MES) approach would reduce the possibility of a type I error, the MES approach proposed by Kling et al. (2007) regresses each component of the index and then obtains a normalized aggregate treatment effect. Following Kling et al. (2007), I first estimate the treatment effect for each outcome, then standardize them, and finally average them. Specifically, the MES of peers' persistence on outcome k in the own-persistence category c is defined as follows: $\text{MES}_c = (1/n_c)\sum_{n=1}^{n_c} e_{kc}/\sigma_{kc}$, 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 is then estimated using the seemingly unrelated regression framework, which accounts for covariance across estimates. See Kling et al. (2007) Web Appendix B for theoretical details.

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 more persistent peers are around, the student is more inclined to agree that she can adjust herself quickly when facing mental stress (column 6) and is more likely to have the educational aspiration of obtaining a college degree (column 7).

Lastly, I investigate whether there are changes in students' self-disciplined behaviors. The CEPS asks two questions related to students' tardiness and truancy: "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 that peer persistence decreases students' tardiness and truancy behaviors. The impact of peer persistence on students' increased self-disciplined behaviors is in line with the psychological root of persistence.[31] In addition, having more self-disciplined students in the classroom might create a classroom atmosphere where self-disciplined behavior becomes a norm, further strengthening the peer persistence effect. To investigate, I use the extent to which students agree with "the class atmosphere is good" using the same 1-to-4 scale. As column (10) shows, classroom atmospheres also improve when more persistent peers are in the classroom.

One might think about competition among students as an alternative mechanism. For example, knowing that classmates are persistent might lead to increased efforts (e.g., study hours) of the focal student to achieve similar goals, operating as one channel behind the impact of peer persistence on student achievement. However, Panel A of Table A6 shows peer persistence does not impact students' self-reported time use on study and entertainment, suggesting that competition among students is unlikely to be one channel through which peer persistence affects student achievement. The results are also consistent with findings

[31] In the Big Five model, both persistence and self-control are considered as correlated facets with Conscientiousness, which is 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 students' academic achievement (Duckworth et al., 2007; Duckworth and Gross, 2014).

in Golsteyn et al. (2021) that show no impact of persistent peers on college students' self-reported study hours.

Table 5: Impacts on 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)
Peer persistence	0.057	0.105***	0.124***	0.111**	0.095**
	(0.041)	(0.038)	(0.043)	(0.045)	(0.038)
Own persistence	0.159***	0.187***	0.204***	0.215***	0.184***
	(0.026)	(0.024)	(0.020)	(0.024)	(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*	0.050**	-0.039***	-0.024**	0.076*
	(0.022)	(0.019)	(0.014)	(0.009)	(0.039)
Own persistence	0.058***	0.016*	-0.042***	-0.005	0.087***
	(0.020)	(0.009)	(0.014)	(0.009)	(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 uses students' own persistence in grade 7 as the dependent variables, Panels B and C discuss variables related to students' perseverance-related attitudes and self-disciplined behaviors, respectively. In Panel A, the three items (columns 1-3) and the average (column 4) of grade 7 persistence are standardized over the estimation sample to have a zero mean and one standard deviation. The MES (column 5) refers to the "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-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. $***p < 0.01, **p < 0.05, *p < 0.1$.

5.2 Teacher Response

Teachers often perform as an important mediating factor between the class environment and students' skill formation. Golsteyn et al. (2021) show that high-quality teachers complement persistent peers in improving student achievement. However, it is unclear whether teachers adjust their behaviors (e.g., becoming more responsible and providing more teaching inputs) in response to a classroom with more persistent students. Understanding how teachers might respond would provide more insight into the complementary relationship between high-quality teachers and persistent peers, as found in Golsteyn et al. (2021). I discuss this potential channel below.

To investigate, I use questions from various modules of the CEPS, including questionnaires for students, parents, and teachers. In the student questionnaire, CEPS asks students to indicate their agreement with the following statements on a scale from 1 (strongly disagree) to 4 (strongly agree): "My headteacher always praises me" and "My headteacher always criticizes me." I create an indicator that equals one if students 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 with their children" on a scale from 1 (not at all) to 5 (very responsible/patient). I create an indicator that equals one if parents believe their children's teachers are responsible/patient or very responsible/patient, and zero otherwise.

As Table 6 shows, students and parents have statistically significant perceptions of teachers being less critical (column 2), and more responsible (column 3) and patient (column 4), suggesting that teachers adjust their behaviors in response to the persistence of their peers in the classroom.

One concern regarding the interpretation of the above results is that they reflect students' and parents' perceptions of teacher behaviors, rather than the actual changes made by teachers. To provide more solid evidence, I analyze whether peer persistence affects teachers' time spent on teaching preparation and grading at the level of subject teachers. CEPS surveys the three subject teachers of each sampled classroom and asks them to report the number of hours spent on teaching preparation and on grading homework and exams during the previous weeks. I take the log value of the reported hours and conduct an analysis at the subject-teacher level, regressing teachers' time spent on teaching preparation/grading on the classroom-level average of peer persistence.

The results are in columns (5) and (6). When focusing on the time spent by each teacher during the previous week, the results show that teachers spend more time on teaching preparation when there are more persistent students in the classroom. The time spent on grading also increases, albeit not statistically significant.[32] While the results reveal that teachers increase their time spent on teaching preparation in response to having more persistent students in the classroom, caution should be exercised in interpreting the results. For example, while this finding could be interpreted as one of the mechanisms through which peer persistence affects students' achievement, it could also be seen as a consequence of increased student achievement. Reduced-form analysis, however, is limited in disentangling these two potential interpretations.

Table 6: Impacts on 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	-0.020*	0.016*	0.017*	0.512**	0.352
	(0.018)	(0.011)	(0.009)	(0.009)	(0.240)	(0.255)
Own persistence	0.043***	-0.021***	-0.002	0.006	–	–
	(0.014)	(0.007)	(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 whether their headteacher praises and criticizes them, while Columns 3 and 4 employ parents' perception of whether their child'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 the time spent on teaching preparation and on 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. $***p < 0.01, **p < 0.05, *p < 0.1$.

[32] Alternatively, one might wonder if parents also play a role when having more persistent students in the classroom. In Table A6 Panel B, I test whether there are any changes in parental investment in response to the presence of more persistent peers and find no effects.

5.3 Endogenous Friendship Formation

Carrell et al. (2013) informed the literature about the important role of endogenous peer group formation in shaping how peers 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*.[33] Since persistent students tend to be those with better academic performance and more self-disciplined behaviors, the formation of friendships with persistent peers could create a better learning environment that facilitates the focal student's learning.

To empirically test the hypothesis, I draw on questions surveyed by CEPS on students' up-to-five best friends and the behaviors of these 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; and 10) dropping out of school. Although the information about who these best friends were is not publicly available, I exploit the behavioral descriptions of best friends to study how peer persistence could affect the focal student's friendship characteristics. Specifically, I create a dummy variable for each behavior description with a value of one indicating at least one of the up-to-five best friends fitting into that behavior and a value of zero 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 that more persistent peers in the classrooms could: i) increase the likelihood of forming friendship

[33]Homophily has been widely studied in the formation of friendships, both in psychology (Selfhout et al., 2010; Wrzus et al., 2017) and in the economics literature (Jackson, 2010).

networks with students who have good grades or aspire to college (columns 1-3); ii) decrease the likelihood of forming a friendship with disruptive peers who are fighting 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 having at least one best friend with good grades. Still, having a one SD increase in peer persistence significantly increases the likelihood of making at least one best friend with good grades by 0.015, which is a precisely estimated 1.58%-increase in the percentage compared to the dependent variable mean.

Although impacts on 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 good grades or engaging in 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% of students in the estimation sample report that they have at least one of up-to-five best friends from their class.[34]

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.[35] To circumvent this, I use the idea of *homophily* to provide a fuller picture behind the findings in Panel A. If the friendship

[34]One might wonder whether having more persistent peers leads the focal student to nominate more (or fewer) best friends, mechanically making the student more (or less) likely to have a friend with certain characteristics. However, the estimated results indicate that peers' persistence does not impact the number of nominated best friends (mean effect size is 0.004, and standard deviation is 0.047, with a dependent variable mean of 4.486). Furthermore, there are no heterogeneous effects on the number of nominated best friends, thus ruling out this alternative interpretation.

[35]Note that using rough friendship measures could lead to a reflection problem. For instance, while having more persistent peers affects the focal student's friendship formation within her class (which is likely given that most best friends are from the same classroom), the student's peers could also be more persistent because they were exposed to a very similar treatment (which includes the treatment effect of the focal student's persistence). This issue could be addressed if we observe the actual friendship network information, where we can identify actual friends in the network and separate them from other peers in the classroom. However, the availability of data limits my investigation of this concern.

formation mechanism is true, then *homophily* could be the driving force behind the effect on friendship characteristics. In other words, when having peers with higher persistence, we should expect high-persistence students to receive more prominent impacts on their friendship characteristics, vis-à-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 receive more prominent impacts on friendship characteristics. 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 friendships with "bad" peers who misbehave (e.g., perform truancy, disciplinary action, fight, smoking or drinking, and go to the net cafe).[36] Results in Panel B also reconcile the heterogeneous analysis showing that having more persistent peers raises the academic performance more for high-persistent students, indicating that friendship formation among persistent peers functions as one underlying mechanism.

Persistent students tend to be those who have good grades (Table 3), aspire to attend college (Table 5 Panel B), and are more self-disciplined (Table 5 Panel C). Therefore, when students with similar levels of persistence are more likely to interact with each other (referred to as *homophily*), it could lead to the formation/sorting of specific networks that will facilitate the focal student's learning.[37] As a result, it gets easier for a persistent student to improve achievement when other students in the classroom also demonstrate persistence in their learning. These findings align with the discussion on how the formation of peer groups,

[36] While the outcome measure ("having at least one friend with the characteristic") captures how peers' persistence affects the student's friendship characteristics on the extensive margin, one would wonder whether the results remain robust when using the original measure the CEPS provides, which is a scale of 0 (none of them), 1 (one or two of them), and 2 (most of them). Table A7 shows robust patterns when using the alternative measure.

[37] In addition to the *homophily* hypothesis, a recent study by Calvano et al. (2022) provides evidence indicating endogenous segregation as another driver that could affect peer interactions. Calvano et al. (2022) finds that, while both low and high-ability students are likely to make friends with higher-ability peers, only high-ability students are getting responses, leading to endogenous segregation among students. If persistence works a similar way as ability, endogenous segregation would also lead to a pattern consistent with the one in Table 7 Panel B. However, not having detailed information on how networks evolve over time in the CEPS limits the investigation of the endogenous segregation hypothesis in this study.

Table 7: Impacts on Friendship Sorting

	"Good" peers network			"Bad" peers network						
	Good grade	Hard working	Aspiration to college	Truancy	Disciplinary action	Fight	Smoking or drinking	Net cafe	Love relationship	Dropout
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Linear-in-mean model										
Peer persistence	0.015**	0.012	0.014**	-0.003	-0.016	-0.021**	-0.014*	-0.011	-0.007	0.008
	(0.007)	(0.007)	(0.006)	(0.007)	(0.011)	(0.010)	(0.007)	(0.008)	(0.009)	(0.006)
Own persistence	0.015***	0.019***	0.007*	-0.010*	-0.025***	-0.031***	-0.019***	-0.034***	-0.044***	-0.002
	(0.005)	(0.006)	(0.004)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(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	0.004	0.014	0.002	-0.001	-0.013	-0.007	-0.006	-0.005	0.009
	(0.011)	(0.009)	(0.010)	(0.012)	(0.016)	(0.013)	(0.012)	(0.012)	(0.014)	(0.007)
Peer persistence*medium persistence	0.012	0.007	0.001	0.007	-0.016	-0.013	0.001	0.002	-0.002	0.018**
	(0.008)	(0.009)	(0.006)	(0.009)	(0.016)	(0.013)	(0.010)	(0.011)	(0.014)	(0.008)
Peer persistence*high persistence	0.015**	0.019**	0.019**	-0.012*	-0.027**	-0.032**	-0.026***	-0.021**	-0.012	0.003
	(0.007)	(0.009)	(0.007)	(0.007)	(0.011)	(0.012)	(0.009)	(0.009)	(0.013)	(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. $***p < 0.01, **p < 0.05, *p < 0.1$.

driven by endogenous factors, can impact the implication of optimal policy design on human capital formation, as highlighted in Carrell et al. (2013).

6 Conclusion

I exploit the student-classroom random assignment and use a nationally representative sample of middle school students in China to study the peer effect of persistence on student achievement and the underlying mechanisms. I document the positive impacts of peers' persistence on students' academic performance in both baseline and follow-up waves. The impact on achievement is greater for students with medium and high levels of persistence.

Investigations into the mechanisms reveal three sets of findings. When having more persistent peers around: 1) students increase their own persistence, perseverance-related attitudes, and self-disciplined behaviors in terms of 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 fewer "bad" peers who exhibit disruptive behaviors. I also document *homophily* that reconciles why having more persistent peers increases the academic performance of students with medium and high levels of persistence to a greater extent.

Uncovering the peer effect of persistence and its mechanisms has significant policy implications. This finding sheds light on the design of optimal assignment policies (Carrell et al., 2013). On the one hand, researchers should consider the endogenous formation of peer networks due to the similarity of characteristics (e.g., personality traits) among students when designing peer-based optimal assignment policies. On the other hand, the heterogeneity analysis in this study indicates that high-persistence students gain additional benefits when surrounded by more persistent peers. This finding suggests a potential policy action for educators and school administrators. For instance, teachers could assign students with similar levels of persistence to the same study groups. This approach could help high-persistence students in the group better overcome academic difficulties regardless of their abilities, thereby enriching the learning environment and interactions, and potentially leading to an overall improvement in academic performance in the classroom.

The discussion in this study also sheds light on the mechanisms behind mindset-based interventions (Alan et al., 2019), offering two insights for policymakers and researchers. First, one must consider spillover effects to fully evaluate the effectiveness of a mindset-based intervention program. Second, when implementing mindset-based interventions to enhance personality traits such as persistence, additional benefits could be realized by providing interventions to groups of students who will later enhance their persistence and academic abilities through the spillover effect, rather than to individual students. I see these implications as promising avenues for future research.

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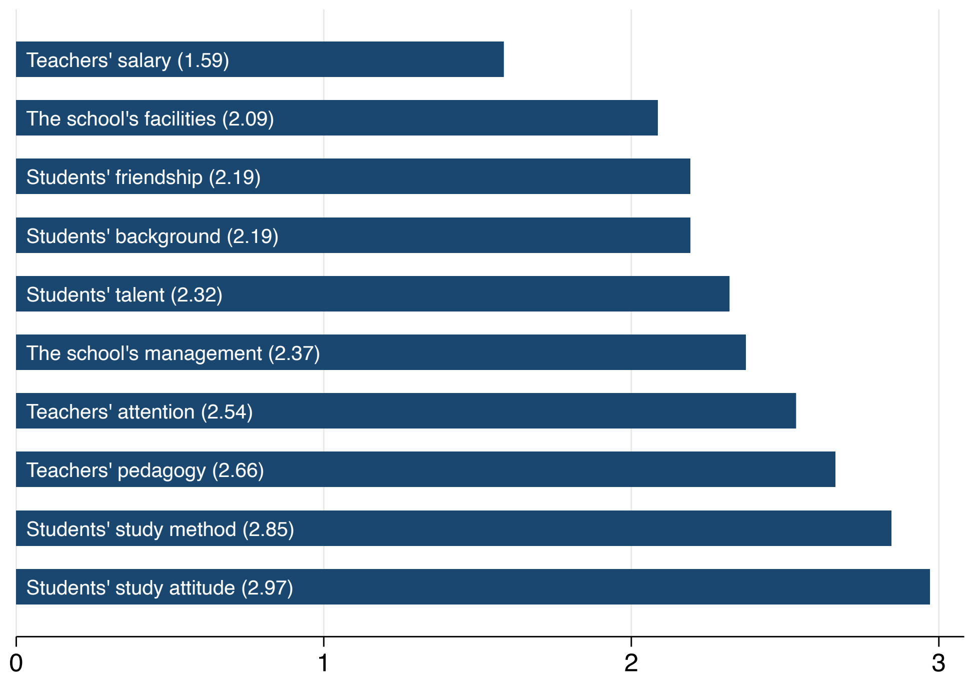
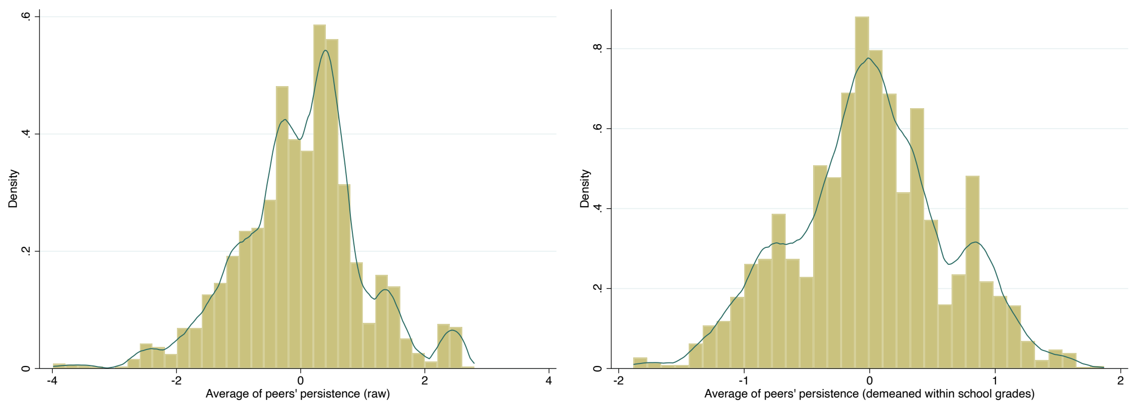
Appendix Figure and Table

Figure A1: Teachers' Perception of Factors Related to Student Achievement



Notes: The figure presents teachers' responses to "To what extent do you believe the following factors are related to students' grades?", rated on a scale of 1 (almost irrelevant), 2 (some relevance), and 3 (closely related). The factors include students' talent, study attitude, study method, family background, friendship networks, teachers' pedagogy, attention to students, teachers' salary, school management, and school facilities. The sample comprises all surveyed teachers at the baseline who responded to this question (N = 1,243), with the mean responses for each factor shown in parentheses.

Figure A2: Variation of Class-Level Persistence within Each School-Grade Cell



(a) Unconditional variation **(b) Residualized variation**

Note. Figure A2a plots the histogram of average of individual-level peer persistence. Figure A2b plots the histogram of residualized average of individual-level peer persistence, demeaned within each school-grade cell. The associated kernel density estimate is added to the graph.

Table A1: Sample Selection Procedure

	Sample size		
	School	Class	Student
Raw data	112	438	19,487
School sample selection			
1. Keeping schools with a random assignment policy	59	115	5,235
2. Dropping schools with re-assignment in grade 8	52	100	4,491
Student sample selection			
3. Dropping students who switch classrooms in grade 8	52	100	4,160
4. Dropping students whose key variables are missing	52	97	3,242
School sample selection			
5. Dropping schools with only one surveyed class	45	90	3,051
Estimation sample	45	90	3,051

Notes. The table details the changes of sample size (of schools, classes, and students) during the sample selection procedure, from the raw data to the estimation sample. See section 2 for the details of the sample selection procedure.

Table A2: Alternative 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 the 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 A3: Balancing Tests for Head Teacher Assignment

	Class level average of persistence	
	(1)	(2)
Age	0.001	0.004
	(0.017)	(0.025)
Female	0.103*	0.135
	(0.057)	(0.083)
Marriage status	-0.151*	-0.194
	(0.081)	(0.191)
Have a college degree	-0.136**	-0.066
	(0.057)	(0.124)
Teaching experience in years	0.001	-0.003
	(0.016)	(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 an estimation 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 A4: Falsification Tests: Peer Characteristics and Student Retrospective Measures

	Panel A. Persistence in grade 6		
	School attendance	Disliked homework	Challenging homework
	(4)	(5)	(6)
Proportion female peers	0.484	-0.175	-0.249
	(0.622)	(0.422)	(0.413)
Proportion migrant peers	-0.362*	-0.135	-0.014
	(0.212)	(0.171)	(0.125)
Proportion low-achieving peers	-0.474	-0.556	-0.708
	(0.386)	(0.369)	(0.444)
Proportion college peer mothers	0.201	-0.060	-0.043
	(0.289)	(0.297)	(0.286)
Peer persistence	-0.013	-0.041	-0.015
	(0.042)	(0.042)	(0.044)
School-grade FE	✓	✓	✓
Mean of dep. var.	3.411	3.438	3.560
Observations	3,051	3,051	3,051
	Panel B. Self-assessment in grade 6		
	Chinese	Math	English
	(1)	(2)	(3)
Peer persistence	0.040	-0.019	0.027
	(0.049)	(0.043)	(0.039)
Own persistence	0.075***	0.056***	0.125***
	(0.021)	(0.015)	(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

Notes. The dependent variables in Panels A and B are students' retrospective measures on persistence and self-assessment in grade 6, respectively. In Panel A, each estimate is obtained separately by regressing the retrospective persistence on one of the peers' characteristics, including the proportion of female, migrant, low-achieving peers, and college-educated peer mothers, as well as the standardized average of peers' persistence. In Panel B, '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. All regressions 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 A5: Impacts of Peers' Persistence on Academic Outcomes: Bounding Exercises

	Std. test score						
	Baseline results	Self-assessment in grade 6	Proportion of accelerated peers	Peers' average of self-assessment	All additional ability controls	Subject teacher sample	
						Baseline controls	Subject teacher controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. grade 7							
Peer persistence	0.095***	0.098***	0.094***	0.103***	0.100***	0.080**	0.065*
	(0.029)	(0.028)	(0.028)	(0.034)	(0.032)	(0.032)	(0.033)
Own persistence	0.094***	0.086***	0.093***	0.095***	0.086***	0.091***	0.089***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Effect bounds and deltas	[0.095, 0.250]						
	$\delta = 6.1440$						
R-squared	0.103	0.198	0.103	0.104	0.198	0.103	0.104
Observations	9,153	9,100	9,153	9,126	9,078	8,538	8,538
Panel B. grade 8							
Peer persistence	0.127***	0.130**	0.123***	0.129***	0.123***	0.107***	0.100***
	(0.027)	(0.027)	(0.026)	(0.030)	(0.029)	(0.028)	(0.031)
Own persistence	0.099***	0.092***	0.098***	0.100***	0.092***	0.096***	0.095***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)	(0.014)
Effect bounds and deltas	[0.127, 0.314]						
	$\delta = 7.7271$						
R-squared	0.114	0.196	0.115	0.114	0.197	0.115	0.116
Observations	9,153	9,100	9,153	9,126	9,078	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 **?**. Columns (2) to (5) add additional control to baseline specification, where column (2) adds self-assessment in grade 6, column (3) adds proportion of accelerated peers, column (4) adds peer average of grade 6 self-assessment, and column (5) includes additional ability controls in columns (2) to (4). Columns (6) and (7) use the sample with no missing values in all subject teacher controls. While Column (6) uses the baseline specification that uses headteacher controls, Column (7) uses the subject teacher controls. Panels A and B show results for achievement 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 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 the school-grade level are in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A6: 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	-0.021	-0.003	-0.026
	(0.020)	(0.021)	(0.022)	(0.027)
Own persistence	-0.006	0.002	-0.039***	-0.061***
	(0.013)	(0.011)	(0.012)	(0.012)
Mean of dep. var.	1.103	0.396	0.602	0.459
R-squared	0.144	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	-0.002	-0.000	-0.020
	(0.041)	(0.015)	(0.033)	(0.031)
Own persistence	-0.027	0.019	0.019	0.042*
	(0.018)	(0.012)	(0.023)	(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 are students' weekly time used in study and entertainment, as measured using the log(hours+1). The dependent variables in Panel B are parental investments in time and two parenting styles. '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 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 the school-grade level are in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A7: Impacts of Peers' Persistence on Friendship Sorting, using Alternative Measures

	"Good" peers network			"Bad" peers network						
	Good grade	Hard working	Aspiration to college	Truancy	Disciplinary action	Fight	Smoking or drinking	Net cafe	Love relationship	Dropout
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Linear-in-mean model										
Peer persistence	0.004	0.033*	0.028*	-0.007	-0.020	-0.023*	-0.018*	-0.016	-0.009	0.006
	(0.020)	(0.018)	(0.014)	(0.009)	(0.013)	(0.012)	(0.010)	(0.011)	(0.011)	(0.008)
Own persistence	0.043***	0.071***	0.043***	-0.010	-0.032***	-0.042***	-0.028**	-0.041***	-0.053***	-0.001
	(0.013)	(0.014)	(0.009)	(0.008)	(0.010)	(0.010)	(0.011)	(0.010)	(0.013)	(0.004)
R-squared	0.100	0.106	0.117	0.070	0.078	0.084	0.065	0.109	0.073	0.034
Panel B. Heterogeneous effects										
Peer persistence*low persistence	-0.006	0.007	0.019	-0.003	-0.004	-0.012	-0.010	-0.009	-0.004	0.007
	(0.029)	(0.029)	(0.022)	(0.014)	(0.017)	(0.016)	(0.014)	(0.015)	(0.017)	(0.008)
Peer persistence*medium persistence	-0.012	0.014	0.021	0.009	-0.012	-0.011	0.005	0.001	-0.001	0.024**
	(0.027)	(0.021)	(0.016)	(0.011)	(0.017)	(0.014)	(0.015)	(0.013)	(0.015)	(0.012)
Peer persistence*high persistence	0.011	0.051**	0.031*	-0.019*	-0.037**	-0.039**	-0.037**	-0.032**	-0.019	-0.003
	(0.020)	(0.019)	(0.016)	(0.011)	(0.015)	(0.016)	(0.014)	(0.013)	(0.015)	(0.009)
R-squared	0.103	0.111	0.120	0.072	0.081	0.087	0.069	0.111	0.074	0.036
School-grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Student controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Teacher controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Peer controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean of dep. var.	2.460	2.489	2.723	1.049	1.090	1.091	1.048	1.079	1.123	1.027
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, how many of these friends have the following behaviors, using a scale of 0 (none of them), 1 (one or two of them), and 2 (most of them). 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. $***p < 0.01, **p < 0.05, *p < 0.1$.