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ABSTRACT

How Good Am I? Effects and Mechanisms behind Salient Ranks*

How can individuals respond to their ordinal ranking when they are not aware of it? We present evidence on the effects and mechanisms of achievement rank effects in middle schools when ranks are salient to students and their parents. For identification, we rely on the random assignment of students (and teachers) to classrooms in China. That is, students with the same baseline test scores end up having different achievement ranks in their assigned classroom. We find positive and large effects of being assigned a higher rank on subsequent performance, especially for males and overconfident students. We show that students with higher ranks spend more hours on autonomic studying. What drives these effects is still an open question, especially when ranks are salient to both students and their parents. Using rich survey data, we show that these academic gains are not only mediated through (1) students' higher self-perception and higher subject learning confidence, but also through (2) better parental understanding of their child's ranks, stricter parental requirements for their child's study, and higher parental expectations regarding their child's educational attainment and career prospects. We show that these two channels make similar contributions to explaining salient rank effects, and when combined they explain 46.80% of the increase in test scores. We find no impact on teachers' investment or attention to students as a result of rank effects.

JEL Classification: I21, J24

Keywords: achievement rank, salience, quasi-random classroom assignment, mechanisms, survey data, middle schools, mediation analysis

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* We would like to thank Haishan Yuan, KK Tang, David Smerdon, Satoshi Tanaka, Jan Feld, and participants in the 2022 Australian Gender Economics Workshop at the Australian National University, the 2022 BEST Conference at the Queensland University Technology, and the University of Queensland for helpful comments. We also thank participants that voted and awarded this paper a Best Paper Award at the 2022 Labour Econometrics Workshop at the University of Wollongong. This project has been reviewed by the Office of Research Ethics and is deemed to be exempt from ethics review. Clearance Number: 2020002332.

1 Introduction

How one's characteristics, abilities, and achievements compare with those of others has long been of interest to social scientists, educators, and policymakers. While individuals may be expected to perform better when they are in a peer group with high-performing individuals, this effect may be offset by a potential tendency to do better when they rank higher than their peers. In education, recent evidence shows that ordinal rank matters substantially for students' subsequent performance, likelihood to finish high school and attend college. In particular, ranking higher in the classroom has a positive impact on students' educational outcomes later in life (Delaney and Devereux, 2019; Denning et al., 2021; Elsner and Isphording, 2017, 2018; Elsner et al., 2021; Murphy and Weinhardt, 2020).

A common issue with those studies is that they often rely on the assumption that students may be aware of their relative standing due to repeated interactions with their classmates, and thus their ordinal rank may be salient to them (Delaney and Devereux, 2019, 2022). However, student rankings are not often public and students are rarely provided with information about those rankings (Delaney and Devereux, 2019, 2022; Goulas and Megalokonomou, 2021). Some students may have a better understanding of their rank than others. A relevant question, then, is: If students do not know their ranking, how can they respond to it? Information on rank as perceived by the students is not often available, and thus existing studies cannot easily estimate the extent to which actual ranks and the ranks perceived by students differ.

When we think about the salience of ranks in education, it is meaningful to think about two different types of ranks: the ability rank and the achievement rank. Whereas the former ranks a student's innate ability, the latter ranks the student's academic achievement as reflected by academic examinations. Compared with ability rank, the advantage of using achievement rank is that academic achievement is likely to be more salient than inherited ability, since students and teachers may be more aware of the (scholastic) performance of other students, as revealed by repeated testing (Delaney and Devereux, 2022). On the other hand, the salience of ability rank is a main issue, since ability ranks are less likely to be communicated among school participants.[1] To our knowledge, this paper is the first to exploit a setting in which achievement ranks are salient to students and parents and to examine the relationship between self-perceived and objective achievement ranks.

This paper examines the effects of salient achievement ranks on students in middle high schools in China and explores the potential mechanisms behind those effects. In this institutional setting, it is common for teachers to communicate students' relative performance or rank directly to students and their parents due to its highly competitive nature (OECD, 2016). To obtain identification, we rely on the within-school random assignment of students to classrooms. This randomization process leads to

[1] An exception is Elsner and Isphording (2017), who study the impact of ability ranks on students' later outcomes by exploiting across-cohort variation. They provide supporting evidence of the salience of ability ranks by showing a positive relationship between cognitive ability rank and the probability of one's self-belief that their intelligence is above average.

idiosyncratic variation in the ordinal achievement rank of students with the same baseline achievement. Therefore, students of the same baseline test scores end up having different achievement ranks due to the slightly different distributions of baseline test scores in the random set of students who are grouped together.

In the first part of the paper, we examine the correlations between achievement ranks and self-perceived ranks. We then study the impact of achievement ranks on subsequent student performance. To do so, we use data from the China Education Panel Survey (CEPS); This is a nationally representative survey of middle school students and their teachers and parents, combined with information on test scores in core subjects (i.e., Chinese, English, and mathematics) from school archives of seventh and eighth graders. Then, we examine whether students with higher ranks spend more time on autonomic studying after school. In the second part, we explore the potential mechanisms through which achievement ranks may affect test scores and perform mediation analysis to quantify the relative importance of these channels in explaining rank effects. In particular, we focus on three main channels: (1) students' self-perception and subject learning confidence; (2) parental perceptions of their child's ranks, requirements for their child's study, and expectations regarding their child's educational attainment and career prospects; and (3) teachers' attention and praise and questions they ask of students.[2]

First, we find a strong and positive correlation between the objective and the perceived achievement rank (as perceived by both students and parents). This provides additional evidence that we are exploiting an institutional setting in which rank effects are indeed salient. We then find that a student's achievement rank in the classroom has a strong impact on their academic performance in the subsequent period, conditional on student baseline test scores. In particular, a 1-standard-deviation increase in a student's achievement rank in grade 7 would on average increase grade 8 test scores by 0.06 standard deviations. This magnitude is in line with estimated rank effects found in other studies that use data from the US and UK (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020). Estimated effects are mainly driven by overconfident students and are more pronounced for males than female students. We then find a positive relationship between student rank and hours spent on autonomic studying. A 10-percentile increase in achievement rank would lead to an increase in student autonomic studying hours by 11% compared with the mean, which translates to an additional half an hour per week. We

[2] Yu (2020) also studies rank effects using the CEPS data. There are important differences between our and their approach. First, Yu (2020) focuses on students' cognitive ability ranks (derived from CEPS-specific cognitive ability tests), while we study the effect of students' achievement ranks (derived from students' scholastic performance in school). It is unclear how cognitive ability ranks may be salient to students when they rely on ability tests performed within the CEPS survey, which are not communicated with any other school participant. Second, Yu (2020) examines the mechanisms behind ability rank effects through investigating the effects of self-perceived rank on the potential mechanism variables conditional on a student's cognitive ability rank. Our approach alleviates concerns of endogeneity when we investigate the potential mechanisms behind achievement ranks. This is because we still exploit the idiosyncratic variation in a student's objective achievement rank that stems from the quasi-random assignment of students to classrooms. This also allows us to perform a mediation analysis to quantify directly the importance of each mechanism in explaining the achievement rank effects that are identified in our main analysis.

also find that rank effects demonstrate a nonlinear pattern: Students who rank near the bottom of the class perform significantly worse relative to those ranking around the median of the class, while students who rank close to the top gain slightly more.

Our second set of results yield some novel findings on the mechanisms behind positive rank effects. We find that rank effects are not merely associated with a change in students' self-beliefs (i.e., higher self-perception in achievement rank and subject learning confidence), which is documented in previous literature, but can also be explained by the rise in parental beliefs about their child's relative performance (i.e., higher parental perception of their child's ranks, stricter requirements for their child's study, and higher expectations regarding their child's educational attainments and career prospects). This is particularly relevant when parents are aware of their child's ranks, which is the case in this institutional setting. Mediation analysis shows that those two channels make similar contributions to explaining rank effects, and together they explain 46.80% of the estimated rank effects. However, we find no impact on teachers' investment in students in response to achievement ranks.

We perform a number of robustness and simulation exercises to verify the internal validity of our identification and rule out confounding factors already suggested in prior literature (e.g., measurement error in baseline and outcome test scores) or neglected (e.g., time-varying confounding factors such as personal traits). We further alleviate concern regarding spurious relationship between ranks and baseline achievement through a Monte Carlo simulation exercise. In particular, we find that the estimated rank effects are null on average after we reshuffle individuals' classmates composition within schools.

To the best of our knowledge, this is the first paper to provide evidence of the salience of student achievement ranks among students and parents and the impact of salient achievement ranks on later outcomes. Previous literature on rank effects usually assumes awareness of ranks (achievement or ability) by the peer group, with little scientific evidence to support this (Delaney and Devereux, 2022). This literature exploits changes in the cohort composition either within schools or within school and subjects over time to estimate rank effects (Delaney and Devereux, 2019; Denning, Murphy, and Weinhardt, 2021; Elsner and Isphording, 2017, 2018; Goulas, Megalokonomou, and Zhang, 2022; Murphy and Weinhardt, 2020).[3] One concern, as noted, is the credibility of estimated rank effects without verifying the awareness of ranks. In addition, the extent to which the awareness is accurate in a large peer group (e.g., cohort peers) is also unknown; Cohort peers may only serve as a rough approximation of one's actual interaction group (Xu et al., 2020), and students may be more likely to interact intensively in a small peer group, such as classmates, to make social comparisons and infer their relative performance (Chetty et al., 2011; Gong et al., 2021; Hu, 2015; Pagani et al., 2021; Zolitz and Feld, 2017). A second concern is that individuals' peer composition may not be formed in a randomized

[3]Apart from the rank effect literature, many peer effect studies exploit within-school-across-cohorts variation in peer composition, such as Bifulco, Fletcher, and Ross (2011); Brenøe and Zölitz (2020); Carrell and Hoekstra (2010); Goulas, Megalokonomou, and Zhang (2018); Hoxby (2000); Lavy, Paserman, and Schlosser (2012); Lavy and Schlosser (2011); Mouganie and Wang (2020).

way. Potential nonrandom sorting of a student in the school cohort or classroom, which might be correlated with ranks through unobserved factors, could introduce bias in the estimated rank effects.[4] We contribute to this literature by using a setting in which rank effects are potentially salient to all students and by exploiting a quasi-experimental setting in which students are randomly assigned to their classmates: A peer group in which they share common courses and intensively interact with each other on a daily basis.

Our second contribution is a deeper understanding of the mechanisms behind estimated rank effects, especially when ranks are salient. Of the evidence so far, most researchers have paid attention to the channels of teachers' investment, effort provision, social learning and students' learning confidence in response to ordinal ranks (Dobrescu, Faravelli, Megalokonomou, and Motta, 2021; Elsner and Isphording, 2017; Goulas and Megalokonomou, 2021; Murphy and Weinhardt, 2020). If anything, they find little evidence that parents respond to their children's ranks. This could be driven by the fact that ranks are not salient and that not all parents have a good understanding of their child's relative achievement rank in these settings. Consistent with other papers, we find that a higher achievement rank is associated with higher subsequent self-perception in achievement rank and higher subject learning confidence by students. This explains around 23.20% of the overall rank effects. Moreover, we contribute to the literature by identifying a novel set of channels related to the change in parental beliefs in response to a child's achievement rank. In particular, we show that parents of higher-ranked students have a higher parental perception of their child's rank, impose stricter requirements for their child's study, and have greater expectations for their child's education level and career prospects. These channels mediate another 23.60% of the estimated rank effects.[5]

This paper also contributes to studies of nonlinear peer effects in education (Abdulkadiroğlu, Angrist, and Pathak, 2014; Burke and Sass, 2013; Carrell, Sacerdote, and West, 2013; Feld and Zölitz, 2017; Lavy, Silva, and Weinhardt, 2012; Lyle, 2009; Xu, Zhang, and Zhou, 2020). Our paper also contributes to the literature on the impact of feedback on education outcomes (Azmat et al., 2019; Bandiera et al., 2015; Goulas and Megalokonomou, 2021), which suggests that students usually have imperfect information on their absolute ability, and may rely more on feedback or rank information to learn their ability and thus alter their investment in future study.

Lastly, our paper speaks to the literature on the effects of ranks in the workplace on occupational productivity, job satisfaction, and job search intention (Brown, Gardner, Oswald, and Qian, 2008;

[4]A recent literature studies rank effects by exploiting the idiosyncratic variation of classroom ranks (Pagani, Comi, and Origo, 2021) or the random assignment of students to classrooms in schools or teaching sections in college (Bertoni and Nisticò, 2019; Carrillo, Onofa, and Ponce, 2011; Elsner, Isphording, and Zölitz, 2021; Goulas, Griselda, and Megalokonomou, 2022; Yu, 2020). However, none of these studies show evidence that achievement ranks are salient to students or parents or explicitly address the issue of salience.

[5]Our findings also contribute to the growing literature on how parents alter their perceptions and their children's investment when they become aware of their children's achievement levels Andrabi, Das, and Khwaja (2017); Behrman, Fan, Wei, Zhang, and Zhang (2020); Bergman (2021); Cobb-Clark, Ho, and Salamanca (2021); Dizon-Ross (2019); Kinsler and Pavan (2021).

Card, Mas, Moretti, and Saez, 2012; Gill, Kissová, Lee, and Prowse, 2019). The response to one's rank position in the education and industry sectors may differ widely. For instance, Gill, Kissová, Lee, and Prowse (2019) show that workers would exhibit the most effort when being ranked in the last place on Key Performance Indicators (KPI), while Murphy and Weinhardt (2020) and our paper both show that low-ranked individuals in schools are significantly disincentived for learning in the later period. This sharp contrast in rank responses between low-ranked individuals in the school and workplace may have implications for educational policymakers seeking to reformulate performance feedback policies and incentive schemes in schools.

2 Institutional Setting and Data

2.1 The Middle School System and Classroom Assignment

Students are assigned to public schools based on proximity from their registered permanent residence (or *Hukou* in Chinese[6]). After completing a 6-year primary school, students must attend a 3-year middle school, since the compulsory education in China is 9 years. The local government monitors the assignment process to ensure that students are assigned to public middle schools based on zoning. Students are not allowed to enroll in schools in districts different from the one in which they permanently reside.

Students attending the same primary school classroom may have different sets of public middle schools to choose from, depending on their permanent residence. The average primary school sends students to four different middle schools; thus, a student is assigned to a middle school classroom in which most of their classmates are new.[7] To a large extent, this mitigates the reflection problem (Murphy and Weinhardt, 2020).

Once students enroll in a given middle school, they are divided into classes in which they take courses together. As shown in Table 1, students are usually divided into classes of around 45 students. The assignment of students (and teachers) to classes within each school in our sample is quasi-random. The Ministry of Education states that schools should promote an "equal and fair opportunity for all students," and thus more and more schools implement a random assignment process in China. Schools that implement random assignment are not allowed to assign students to classes based on ability, family background, or any other observed characteristics. Students are also not allowed to switch classrooms and are expected to stay in the same class until they graduate. This classroom assignment, which takes place at the beginning of grade 7, allows for a randomization of peer characteristics in the classroom, which we show later.

[6] *Hukou* is an official household registration record that identifies a person's residency status in an area.

[7] According to the Ministry of Education, there are 234,369 primary schools and 54,572 middle schools in China. Statistics are from URL: http://en.moe.gov.cn/documents/statistics/2013/national/201412/t20141215_181591.html.

2.2 Data and Variables

Data on student performance are based on the CEPS (China Education Panel Survey) dataset for the years 2013-2015. The CEPS also includes a series of questionnaires administered by the National Survey Research Center at Renmin University of China. The CEPS covers 112 middle schools in 28 counties and city districts in China.[8] Four schools from each of the 28 counties or cities and students in two classrooms in each grade are randomly selected. The first wave of the survey was conducted in 2013-2014 and students in grade 7 and 9 were surveyed. A follow-up survey was done in 2014-2015 and targeted students who were in grade 7 in the first wave and grade 8 in the second wave. Thus, our sample includes students for whom we have longitudinal information and who completed the survey in grade 7 in 2013-2014 and grade 8 in 2014-2015. The CEPS also includes surveys of parents, teachers, and the school's principal in both waves.

CEPS student data include test scores for seventh and eighth graders in three core subjects—Chinese, math, and English—recorded in the school archives, as well as the responses of the same seventh and eighth grade students to questionnaires. Our main outcome variable is the aggregate performance of students across those three subjects on the midterm exams in grade 8, which we derive by summing a student's test scores in the three related exams. Raw test scores are on a 1-to-450 scale that we transform into z-scores within each class to facilitate interpretation of the results.

The CEPS student questionnaire addresses various aspects of the school and learning environment. We select sections from the questionnaire that focus on the student's own and parental beliefs about their child's scholastic and behavioral outcomes. In these sections, students are asked to report their beliefs on their own achievement ranks in class in grades 6 and 7 of primary school. Students are also asked to rate the extent to which they agree with a series of statements about teachers' investment behavior (e.g., attention, praise, questions) on a 4-point scale ranging from 1 (*strongly disagree*) to 4 (*strongly agree*). We also examine a section on the questionnaire in which students report the amount of time allocated to extra schoolwork. The parent survey includes questions on beliefs about and expectations for their children—and in particular, beliefs about their children's achievement ranks in class, requirements for children's study, and expectations for their children's educational attainments and career prospects. We use students' and parents' responses to these items to examine the potential mechanisms behind rank effects; namely, whether students' ranks within the classroom affect own student's perception, parental beliefs, and teachers' investments. We provide more details on the original survey questions in Appendix D and show how we construct our main variables in Appendix Table A.1.

To ensure that we use data on schools that implement a random classroom assignment policy in grade 7, we use the survey sections for school principals and teachers (i.e., the principals/teachers are

[8]The CEPS is the first and largest nationally representative education survey in China. For more information, see URL: `http://ceps.ruc.edu.cn/English/Documentation/Sampling_Design.htm`. Other studies have also used this data and randomized quasi-experiments to study causal questions (Gong et al., 2018, 2021; Hu, 2015; Xu et al., 2020).

the ones answering the questions), and require that the following conditions are met: (1) the school principal reports that students are randomly assigned to classrooms in grade 7; (2) the school principal reports that the rearrangement of students across classrooms or grades is not allowed after the initial random assignment in 7^{th} grade; and (3) all head and subject teachers in the same grade report that students in the respective grade are not assigned to classrooms by test scores. These are the same conditions as the ones used by Gong, Lu, and Song (2018) to study a different research question.[9] We require an additional condition (4): all students in the school report that they are not assigned to classrooms based on test scores. There are two minor differences between our 7^{th} grade sample size and that of Gong, Lu, and Song (2018). First, we drop 377 observations from 4 schools, due to condition (4). Second, we drop 130 observations from 3 schools that surveyed only one classroom, since schools need to have at least two classrooms in order to exploit cross-classroom variation for identification.

We link students in the two waves based on a unique student identifier and have longitudinal information on students in grades 7 and 8. Our final sample consists of 3,592 students across 92 classrooms in 46 schools. In this sample, around 90% of schools are public. All schools in the sample have mixed-gender classes. We also collect rich demographics on students from the survey to construct measures of students' background and family characteristics. The data contain a unique class identifier, which allows us to identify a student's classmates. This is important, since our variable of interest is a student's achievement rank among their classmates. We compute a student's achievement rank based on their total score on first-semester exams in Chinese, math, and English early in grade 7. We consider this to be the baseline achievement (or baseline test score) students obtained on the earliest exam held in grade 7 and, which takes place shortly after students are randomly assigned to their new classrooms.[10] Students have no way of receiving information about their relative performance prior to this exam, since there is no clear way to compare students' achievement. Interactions between students and teachers are also minimal at this point. To ensure that the rank is comparable across classrooms with different classroom sizes, we normalize the absolute rank to a percentile one. This assigns the value 0 to the lowest-ranked student and the value 1 to the highest-ranked student in the classroom by using the following formula:

$$rank^0_{i,s,c} = \frac{n_{i,s,c} - 1}{N_{s,c} - 1} \tag{1}$$

where $n_{i,s,c}$ is the absolute rank of student i based on the total score on the early 7^{th} grade exam in classroom c and school s.[11] $N_{s,c}$ is the number of students in classroom c and school s. In the case of

[9]Gong, Lu, and Song (2018) focuses on middle school students in China to study the impact of teacher gender on student academic, mental status and social acclimation using the same data.

[10]In a typical Chinese middle school, an academic year is divided into 2 semesters, with semester 1 (or fall semester) commencing at the beginning of September in the current year and semester 2 (or spring semester) commencing in the middle of February in the following year. Each semester usually lasts 20 weeks. Midterm examinations are usually conducted before the 8^{th} week of the first semester.

[11]To construct the percentile rank, we proceed in 2 steps. First, we compute the *absolute rank*. If a classroom has 30

two or more students having the exact same baseline test score within the classroom, our main rank assigns the highest rank to those students.[12] There are two time periods, with notation 0 for 7^{th} and 1 for 8^{th} grade. The rank is calculated in grade 7, and thus only the 0 notation is used in equation (1).

For a given baseline test score in grade 7, the random classroom assignment produces considerable variation in student ranks. In other words, students who have the same baseline test score may end up having a different rank due to random variation in their classmates' baseline performance distribution. We exploit this variation in achievement rank after we control for school-specific test scores and classroom fixed effects.[13] Table A.2 in the Appendix shows that the corresponding standard deviation after we condition on school-specific test scores and classroom FE is 0.101.[14] This suggests that there is substantial variation in achievement ranks across classrooms for the same baseline achievement. In particular, a standard deviation equal to 0.101 translates into roughly 10 percentiles or 5 (45×0.101) absolute rank positions up or down, depending on the random class a student is randomly assigned to.[15]

The predetermined variables we use include: (1) student characteristics such as gender, age, minority status,[16] and pre-middle school scholastic attainment (i.e., an indicator for attending kindergarten, an indicator for skipping a grade in primary school, and an indicator for repeating a grade in primary school); and (2) family background characteristics, including residence information (i.e, an indicator for rural residence[17] and local residence[18]), family income information (i.e, an indicator for high income level), and father's and mother's years of schooling. We later show that the rank is uncorrelated with these predetermined student and family characteristics. Summary statistics for these variables are shown in Table 1. Students are on average 13 years, 50% of students in the sample are females and 57% of students are in a family with only one child. 8% of students are in a high income family, while the average school size is 90 students.

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students, the student achieving the highest total score is assigned a rank equal to 30, and the student with the lowest score is assigned a rank equal to 1. Students with the same scores are assigned the same rank. Then we normalize it to a *percentile rank* using equation (1). The rank ranges from 0 to 1 and has a mean equal to 0.5 (see Table 1).

[12] We consider alternative ways of treating the ties in Section 4.1.

[13] The unconditional standard deviation of the achievement rank in early grade 7 is 0.285 (see Table 1).

[14] We obtain this residual variation of the achievement rank by running a regression of achievement rank on school-specific test scores and classroom fixed effects. Also, Appendix Table A.2 shows the standard deviation of the rank unconditional and conditional on different combinations of controls and fixed effects.

[15] To get this number for a given test score within the school, we multiply the mean classroom size (45 students) by this standard deviation (0.101).

[16] There are 56 ethnic groups in China. Of them, *Han Chinese* is the majority group and accounts for around 91.59% of the Chinese population. The other 55 ethnic groups are thus minority ethnic groups.

[17] Rural residence is a binary indicator that takes the value of one if a student's household is registered in a rural area in China.

[18] Local residence is a binary indicator that takes the value of one if a student is registered in the same district or country as the one in which the student's household is registered.

2.3 Salience of Ranks

An important assumption regarding students' reactions to ranks is the awareness of ranks. Salience is a major issue for the rank literature, as the prior literature usually assumes that students have some understanding of their achievement rank, although they are rarely aware of this information (Delaney and Devereux, 2022). In Chinese middle schools, it is not uncommon for students to be informed about their relative standing in the class due to its competitive nature. Students may know or gauge their class ranks either from interactions among their classmates or from their communication with their subject teachers. Also, parents are often informed about their child's class ranks through the regular parent-teacher conferences (usually right after midterm or final semester exams) or home visitation by teacher. To verify this anecdotal evidence, we use two unique measures of rank beliefs from the perspective of students and parents in CEPS, captured by the following survey questions in semester 1: *"How does your academic record rank in your class at present?"* on the student questionnaire and by *"How does this child's academic record rank in his/her class at present?"* on the parent questionnaire.

Figure 1 shows a strong and positive association between students' self-perception in their own objective achievement rank and their actual objective achievement rank; and between parents' perception in their children's objective achievement rank and students' own objective achievement rank in grade 7. Although these binned scatter points do not perfectly match the 45 degrees line, the correlations are pretty high and equal to 0.75 (for students) and 0.68 (for parents), respectively.

Figure 2 shows two binned scatter plots for the differences between perceptions in achievement ranks (by students and parents) for each percentile of student baseline test scores. If the perceived ranks and the actual ranks were very different, then we would expect to see considerably large values for the differences between those two ranks. Figure 2 shows no significant variation in the differences between a student's self-perception of achievement rank and their actual achievement rank, and between parents' perception in their children's achievement rank and their students' actual achievement rank, for each percentile of student baseline test scores. The bins are all centered about the horizontal line that indicates no differences between the two ranks. These evidence indicate that both students and parents are aware of students' achievement ranks in the classroom. Achievement ranks are in general salient to all students in the class.[19]

Figure 3 presents visual evidence of the relationship between achievement rank in grade 7 and subsequent test scores in grade 8. This relationship shows that increasing the achievement rank from the bottom to the top of the class is associated with a change in subsequent test scores by almost 3 standard deviations. However, this is just a correlational exercise and is unconditional on student baseline achievement and class-level influences.

[19]Details on how the student's and their parents' perception of ranks is constructed is shown in Table A.1. Original survey questions are shown in Appendix D.

3 Identification Strategy

3.1 Econometric Specification

We use the following specification to estimate the effects of student achievement rank in grade 7 on subsequent test scores:

$$y^1_{i,s,c} = \alpha + \beta rank^0_{i,s,c} + \sum_{s'}^{S} G(y^0_{i,s',c})[\mathbf{1}(s' = s)] + X_{i,s,c}\boldsymbol{\gamma} + \eta_c + \epsilon^1_{i,s,c} \tag{2}$$

where i denotes student, c denotes classroom, and s denotes school. $y^1_{i,s,c}$ in the 8$^{\text{th}}$ grade test scores of student i in school s and classroom c (in period $t = 1$).[20] $y^0_{i,s,c}$ denotes the baseline scholastic achievement, which is the early 7$^{\text{th}}$ grade student test score (in period $t = 0$). To account for school heterogeneity in examinations and the potential nonlinear relationship between the baseline achievement and the outcome, we interact each school indicator $[\mathbf{1}(s' = s)]$ (i.e., an indicator function that equals 1 if the student is in school s) with a quartic polynomial of baseline test score $G(y^0_{i,s',c})$.[21] $X_{i,s,c}$ is a vector of students' covariates that includes the student and family characteristics discussed above. η_c is a classroom fixed effect, which is critical for our identification. Including classroom fixed effects accounts for unobserved heterogeneity at the classroom level (i.e., disruption in the classroom on the day of examination),[22] but also absorbs any classroom-level differences in observable characteristics between classrooms, such as classroom-level peer group characteristics and teacher quality.

The coefficient of interest is β, which captures the effect of achievement rank ($rank^0_{i,s,c}$) on subsequent performance. It is identified by comparing the outcomes of students who have the same predetermined characteristics and baseline achievement, except for the fact that they acquire different achievement ranks only due to small differences in classroom baseline achievement distribution. For β to be causally estimated, the treatment variable $rank^0_{i,s,c}$ has to be as good as random, so that the following exogeneity assumption holds:

$$Cov\left(\epsilon^1_{i,s,c}, rank^0_{i,s,c} \;\middle|\; \sum_{s'}^{S} G(y^0_{i,s',c})[\mathbf{1}(s' = s)], \boldsymbol{X}_{i,s,c}, \eta_c\right) = 0 \tag{3}$$

That is, the achievement rank should be randomly assigned to students conditional on η_c, $\boldsymbol{X}_{i,s,c}$, and $\sum_{s'}^{S} G(y^0_{i,s',c})[\mathbf{1}(s' = s)]$. We provide evidence to support the above assumption and discuss potential threats in the following sections.

[20] The outcome variable is transformed into standardized z-scores at classroom level to facilitate interpretation of the results.

[21] In Section 6.4, we further discuss the choice of a quartic polynomial of baseline test scores and the robustness of the estimated rank effects when different polynomials are used.

[22] However, classroom fixed effects cannot absorb individual-level unobserved heterogeneity (e.g., illness on the day of examination), which we examine in detail in Section 6.3.

3.2 Evidence on the Validity of the Identifying Assumption

In this section, we provide evidence that middle schools in the sample use a practically random classroom assignment. We first check whether changes in achievement ranks across classrooms are associated with changes in student or family characteristics. Table 2 provides evidence on these balancing tests. Column 1 shows the estimated coefficients from within-classroom regressions (by including classroom fixed effects) of various student and family characteristics on students' achievement rank in grade 7. We also control for the quartic polynomial of baseline test scores. Achievement rank is not related to most of the observable student or family characteristics; the only exceptions are rural/local residence and maternal education. We check whether these small imbalances happen randomly or are triggered by systematic sorting by performing two more balancing checks.

In column 2, we show that classroom number is not systematically associated with differences in average classroom observable characteristics. In particular, we regress the classroom-level mean of the characteristics listed on the left on a classroom binary indicator (which takes the value of 1 if the current classroom is number 2 and 0 if the current classroom is number 1) and school fixed effects. All estimated effects are small and statistically insignificant. Not surprisingly, these estimates indicate that classrooms within the same school have similar average student and family characteristics.

To further investigate whether there may still exist some concern about sorting, we examine the existence of *passive sorting* (Denning et al., 2021). This happens when a certain type of student is sorted into a peer group with a certain type of baseline test score distribution, thereby generating a spurious relationship between rank and outcomes.[23] To do so, we check whether student characteristics are associated with the variance of their peers' scholastic performance. In particular, we regress each student characteristic listed on the left column of Table 2 on the standard deviation of the (student-specific leave-out) peers' baseline test scores. Column 3 shows that all estimates are practically zero and statistically insignificant. This suggests that there is no *passive sorting* to classrooms, and students with certain characteristics are not systematically sorted into peer groups with a specific test score distribution.

Apart from verifying the random assignment of students, we provide evidence that the assignment of teachers to classrooms is also random. We examine whether there is any correlation between teacher characteristics and mean characteristics of students and their families. In particular, we regress teacher gender and seniority on the classroom-level mean of each student and family characteristic. We do that for each subject teacher (Chinese, math, and English) and the head teacher.[24] Table A.3 shows that

[23] Generally, students with performance above (below) average in a class with a higher variance in baseline test score would have a lower (higher) rank. If an above average student with a certain characteristic (i.e., disadvantaged family income) is systematically sorted in a class with a higher variance, he/she is likely to have a lower class rank, generating a negative correlation between rank and that characteristic. Given that this student characteristic may affect the outcome, such correlation would produce spurious rank effects on the outcome.

[24] Both head and subject teacher are in charge of teaching one subject, but the head teacher is also in charge of class management and organization.

almost all estimates are small and not statistically different from zero. Only 2 out of 96 estimated coefficients are statistically different from zero. This provides evidence that teachers are not systematically allocated to classrooms based on student or family characteristics.

Overall, these results suggest that students (and teachers) are quasi-randomly assigned to classrooms in middle schools in our study sample.

4 Results

4.1 Linear-in-means Rank Effect Model

Table 3 reports the estimated effects of achievement rank on students' subsequent test scores using specification (2). Column 1 shows estimated effects without including controls for student and family predetermined characteristics. In column 2, we include all student and family predetermined characteristics. The estimated effect remains the same (=0.557) and the standard error remains almost unchanged (se=0.186 instead of 0.185).[25] The stability of the estimated effects indicates that we have a well-balanced sample of student and family predetermined characteristics across classrooms, which is not surprising given the random classroom assignment. The estimate in column 2 suggests that a 1-standard-deviation increase in rank would increase a student's subsequent test score by 0.056 (0.56 $\times$ 0.101) standard deviations.

Our estimated effects of achievement rank on test scores are in line with those found in the US and Netherlands (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020). For instance, Murphy and Weinhardt (2020) estimate the effects of students' primary school achievement ranks on their test scores in middle school. They find that a 1-standard-deviation increase in primary school rank increases later test scores by 0.084 standard deviations. Elsner, Isphording, and Zölitz (2021) use data from a university in the Netherlands and find that a 1-standard-deviation increase in the ordinal student rank in their tutorial section increases student follow-up performance by 0.071 standard deviations.

4.2 Nonlinear Rank Effect Model

Rank effects may be nonlinear and students with different ranks may react differently (Denning, Murphy, and Weinhardt, 2021).[26] In particular, we replace the single achievement rank parameter β with

[25] Recall that our measure of achievement rank uses the highest rank for all students who have the exact same baseline test scores within a classroom, while different ways of breaking ties generate similar results. In Table A.4, we break ties to construct alternative ranks using other methods, and the estimated effects are very similar in magnitude. We use the following alternative methods to break ties: (1) mean rank—assigns the average rank for all students tied with the same baseline test scores within the same classroom; (2) low rank—assigns the lowest rank for all students tied with the same baseline test scores within the same classroom; and (3) random rank—assigns a random rank for all students tied with the same baseline test scores within the same classroom.

[26] Figure 3 provides suggestive evidence that rank effects may be nonlinear. For instance, moving from the bottom to the 40$^{\text{th}}$ percentile in rank improves subsequent performance by approximately 2 standard deviations. However, the

indicators for the 20 ventiles of the achievement rank distribution in the specification as follows:

$$y^1_{i,s,c} = \sum_{r=1,r\neq 10}^{20} \mathbf{1}(rank^0_{i,s,c} = r)\rho_r + \sum_{s'}^{S} G(y^0_{i,s',c})[\mathbf{1}(s' = s)] + \boldsymbol{X}'_{i,s,c}\boldsymbol{\gamma} + \eta_c + \epsilon^1_{i,s,c} \tag{4}$$

where the indicator function $\mathbf{1}(rank^0_{i,s,c} = r)$ takes the value 1 if an individual i 's $rank^0_{i,s,c}$ falls into the r^{th} ventile of the rank distribution in classroom c and 0 otherwise. The reference group is the 10$^{\text{th}}$ ventile, which consists of students who rank at the median of the distribution (i.e., those who rank from the 45$^{\text{th}}$ to the 50$^{\text{th}}$ percentile). Parameter ρ_r captures a student's gains in test scores relative to their peers at the median of the class.

Figure 4 plots these point estimates ρ_r and the corresponding 90% confidence intervals, with the vertical line representing the median of the class (the reference group). The pattern shows a general increase in scholastic gains with achievement rank. Estimated rank effects are positive and marginally significant for students who rank above the 12$^{\text{th}}$ ventile (or 60$^{\text{th}}$ percentile) in the classroom; rank effects become negative and statistically significant for students who rank below the 5$^{\text{th}}$ ventile (or 25$^{\text{th}}$ percentile). Although scholastic gains are approximately monotonically increasing in rank, the effects exhibit a nonlinear trend with marginal diminishing returns.

We then use nonlinear specification (4) to investigate potential heterogeneity by gender by adding interactions of gender and the set of rank indicators $\mathbf{1}(rank^0_{i,s,c} = r)$. Figure 5 presents estimates ρ_r and their corresponding 90% confidence intervals for both genders. The pattern shows a nonlinear trend for both genders, with a slightly steeper slope for males than females who rank above the median of the class. This suggests that males may be more positively affected at the top of the rank distribution than females, although this result may be imprecise.

The higher gains for males from being high-ranked may be due to the fact that males perceive themselves to be higher ranked than they actually are (Murphy and Weinhardt, 2020). We actually provide evidence on this conjecture by visualizing the distributions of self-perceived versus actual achievement rank by gender. Panel (A) in Figure 7 shows that the distribution of achievement ranks for males is skewed to the right while that of their self-perceived achievement rank is slightly skewed to the left; the means of perceived and actual achievement ranks differ by 7.6 percentiles. Male students seem to be over-confident, especially when their actual achievement rank is above the average. For females, on the other hand, actual and self-perceived ranks have more similar distributions, as shown in Panel (B), with the difference in the means of perceived and actual achievement ranks being only equal 2.5 percentiles. Interestingly, female students seem to be under-confident at the bottom and the top of the actual achievement rank distribution.[27]

increment is less than 1 standard deviation when moving from the 40$^{\text{th}}$ percentile to the 80$^{\text{th}}$ percentile.

[27] The nonlinear rank effect pattern found in education is very different from that found in the workplace. For instance, Gill et al. (2019) show that workers exhibit more effort and become more productive in a later period when they are ranked at the bottom or top of their Key Performance Indicator (KPI). Gill et al. (2019) define this as "last-place loathing." They find that the rank response function in the workplace is U-shaped, whereby individuals increase their effort the most after being ranked first or last on performance evaluations.

4.3 Heterogeneous Rank Effects

We now investigate whether students with certain characteristics react differently to ranks. For this purpose, we add an interaction term between a student's achievement rank and student characteristics (i.e., binary indicator for female, binary indicator for minority, binary indicator for high income, father's years of schooling, and mother's years of schooling) in the specification (2). Table 4 shows the results.

Most interaction terms are statistically insignificant, whereas the estimates for achievement rank remain within the range of 0.52-0.66. The only interaction that is statistically different from zero is the one between achievement rank and the binary indicator for female students. This estimate implies that the gains in test scores in grade 8 for males whose 7th grade achievement rank increases by 10 percentiles are 0.02 standard deviations larger than the gains for females, conditional on baseline performance. This suggests that males may be more responsive to rank than females. This is in line with findings by Murphy and Weinhardt (2020) and Bertoni and Nisticò (2019), and is also consistent with the literature on heterogeneous gender attitudes toward competitiveness in a gender-mixed setting (Delaney and Devereux, 2021; Gneezy et al., 2003).[28]

We then examine students' reactions to achievement ranks based on whether students are over or under-confident. To do so, we run our main specification (2) and estimate rank effects separately for students who over perceive and under perceive their achievement ranks early in grade 7. Column 1 in Table 5 shows that rank effects are driven by students who over perceive their achievement ranks. A 10-percentile increase in their rank increases subsequent test scores by 0.01 standard deviations. We report the estimated effects for students who under perceive their achievement ranks in column 2. Estimated effects are almost half in magnitude compared with those in column 1 and imprecise. This implies that our main results are primarily driven by students who are overconfident in evaluating their achievement ranks.

5 Falsification Exercise

One might be concerned that the impact of rank may capture some unobserved confounding factors, such as the underlying true ability in case it is not absorbed by the baseline achievement score. To address this concern, we construct a false peer group for each student by remixing their classmates within the school and recalculating their achievement rank in the false peer group. We first do so for the actual number of classrooms in our sample (=2). We then replace the actual rank with the placebo rank generated by the false peer group and re-estimate specification (2). We repeat the student reassignment and aforementioned placebo rank effect estimations 10,000 times. We also draw the distribution of the actual rank effects as a point of comparison. Panel A1 in Figure 6 shows the distribution of placebo

[28] We also test whether students are more responsive to their achievement rank among their same-gender peers. We do so by replacing the achievement rank with the gender-specific achievement rank in the classroom. We find that the within-gender rank effect is small and statistically insignificant, with an estimate of 0.176 (se=0.168). This indicates that the heterogeneous reaction to ranks by gender is not due to within-gender comparison of relative performance.

rank estimates from the falsification exercise (solid curve) and the distribution of actual rank estimates from our main estimation (dotted curve). The pattern suggests that the estimated placebo rank effect is null, on average, in contrast to the distribution of main rank effect estimates, which are positive. Panel B1 displays the distribution of p-values for the placebo rank estimates shown in Panel A1, which shows that the test rejects at the 5% level approximately 5% of the time, and p-values follow an expected uniform distribution. This indicates that the placebo rank effects at any conventional level (i.e., p-value$<$ 10%) are statistically significant only by chance.

Next, we artificially add one and two hypothetical classrooms in each school in the sample. In particular, we randomly reassign the existing students within each school to 3 or 4 classroom numbers. Now that there is a larger number of classrooms, students are less likely to be assigned to their actual classmates. We then recalculate each student's achievement rank within each school-class and rerun the main specification, while the coefficient of interest is now the estimate of the achievement rank in the false group of classmates. Panels A2 and A3 in Figure 6 plot the placebo rank estimates when there are 3 or 4 classrooms, respectively. There is an increasing probability mass around zero when there are 3 and 4 classrooms compared with Panel A1, when there are only 2 classrooms in each school. In contrast, the distribution of the main rank effects (dashed lines) are not centered around zero and indicate positive average rank effects. In Panels B2-B3 we show the distribution of p-values for the related estimated coefficients. One can reject the null hypothesis of no placebo effects only by chance. These results suggest that our baseline rank effects do not pick up any spurious correlation between the achievement rank and potential confounding factors. This is reassuring and indicates that the estimated rank effects are due to interactions among students in their actual peer groups.

6 Robustness Checks and Additional Results

6.1 Additional Controls

Rank effects may be biased if some individual-level unobservable characteristics have different impacts on baseline and subsequent test scores. For instance, student learning motivation and personal traits may affect test scores in both periods differently. To examine this, we include controls for student pre-middle-school learning motivation in the main specification.[29] We present the estimated rank effect in row 2 of Table 6, while we show the baseline effect as a point of comparison (row 1). The point estimate remains very similar (0.597 instead of 0.557). This suggests that controlling for the baseline

[29]We capture student learning motivation in pre-middle school by students' response to the following statement: (1) the student endeavors to attend school even if not feeling well; (2) the student endeavors to finish homework even if they dislike the subject; and (3) the student endeavors to finish homework even if it is challenging. We use principal component analysis (PCA) on these three responses and then use the first principal component score (standardized) as the pre-middle school motivation measure for each student.

test score probably captures those student-level unobservable factors to a large extent.[30]

Another concern may be that peers' achievement distribution and composition could affect one's classroom rank and subsequent test scores simultaneously. Such variables may be (1) the mean and variance of peers' achievement (Sacerdote, 2001; Tincani, 2017) and (2) the composition of high-achieved or low-achieved peers in the classroom (Bertoni and Nisticò, 2019; Feld and Zölitz, 2017; Lavy et al., 2012; Lyle, 2009).[31] In Table 6 row 3 we control for the mean and standard deviation of a student's peers' baseline test scores and the estimated rank effect remains quite robust (0.531 with se=0.181). In row 4 we partial out nonlinear ability peer effects and the estimated rank effect still remains positive and significant (0.476, se= 0.206), though slightly attenuated.[32]

6.2 Student FE

Row 5 in Table 6 presents the estimated effects from an alternative identification of rank effects by using a within-student fixed effect estimation to control for student-level confounding factors. To obtain within-student variation in rank, we stack observations for the three subjects for each individual. Therefore, our estimation is at student-by-subject level (instead of student level, as in our main analysis). We also control for subject-by-classroom fixed effects and include a school-specific quartic function of baseline subject test scores. The estimated rank effect is now 0.470 and is precisely estimated. This estimate is comparable to our baseline achievement rank effect, although slightly smaller. This is because the inclusion of student fixed effects absorbs any common student-level across-subjects growth in test scores.

The within-student estimation is not our preferred specification, since it assumes that a student's response to their rank is the same across all three subjects. The purpose of this exercise is to provide additional evidence that our rank estimates are not primarily driven by individual-level confounding factors.[33]

[30] To further examine the extent to which student-level unobservable factors may confound the estimated rank effects, we introduce an innate ability-deterministic and time-varying confounding factor in a simulated data generating process (DGP) of student baseline and subsequent performance in Appendix A. Our simulation results indicate that the estimated rank effects identified by our main specification (2) are unbiased and consistent as long as the baseline test score is included in the specification.

[31] In addition, ability peer effects may be heterogeneous in student ability. Low-achieving (or high-achieving) students might be positively (negatively) affected by high-achieving (low-achieving) peers, so that the lower gains from a potential lower rank (compared with higher-ranked students with the same baseline achievement in other classes) might be offset by the positive (negative) peer effects.

[32] We follow the approach of Burke and Sass (2013); Carrell et al. (2013); Zolitz and Feld (2017) and Bertoni and Nisticò (2019) and classify students as high-, middle-, and low-achieved types. We do that based on whether their grade 7 baseline test score is in the top, middle, or bottom third of the baseline test score distribution in the classroom, respectively. We then compute for each classroom the proportion of peers who are high-, and low-achieving and include the interactions of students' own type (high-, middle-, and low-achieved) with the fraction of high- and low-achieving peers in equation (2).

[33] The same concern is also addressed from a different angle in a simulation exercise in Appendix Section A.

6.3 Measurement Error in Test Scores

We then examine the extent to which individual-level measurement error in test score may affect the estimated rank effects. This type of measurement error may produce noise in one's own and other students' baseline achievement. If the measurement error is relatively small in one's baseline test score, then it would only create a noisy measure of one's true ability but preserve one's rank. Rank will capture the underlying students' ability that is not captured by the observed test scores, which creates spurious rank effects. If the measurement error in baseline score is relatively large, it may transit some noise into one's rank, which could potentially lead to attenuation bias. The size of measurement error for deciding the direction of the bias is unclear. Meanwhile, measurement error may also exist in subsequent achievement, even render the direction of bias even unpredictable.

To examine this, we follow and extend the approach of (Murphy and Weinhardt, 2020), and perform two Monte Carlo simulations in measurement error in which we explicitly introduce (1) a test score-independent measurement error and (2) a test score dependent measurement error into either the baseline achievement or both baseline and subsequent achievement. We describe the details of those exercises in Appendix B, but summarize our findings here. We find that a small measurement error (i.e., below 5% of the school-level standard deviation in test scores—equivalent to 2.15 points) has a negligible impact on our estimates in both exercises. However, we observe an attenuation pattern in rank effects as the measurement error increases in the baseline achievement. The attenuation is more salient when the measurement error exists in both baseline and subsequent achievement. This suggests that our baseline rank effect estimate is expected to provide the lower bound of the true effect.

6.4 Flexible Form of Test Scores

The causal identification of the estimated rank effects depends on the correct modeling of the relationship between baseline test scores and the outcome (Denning et al., 2021; Murphy and Weinhardt, 2020). Rows 6-11 of Table 6 show estimated rank effects in which we use increasingly higher-order polynomials of the baseline test scores. Our main results include a quartic polynomial of baseline test scores. We do this to ensure that the rank is not confounded by a misspecification in the functional form. We notice that rank effect estimates are stable (i.e., there is not much difference in rank effects 0.577, 0.677, and 0.617 with a quartic, quintic, and sextic polynomial, respectively) once we include a quartic relationship between baseline test scores and outcomes. Thus, we use the quartic polynomial as our preferred specification.

6.5 Rank Effects on Autonomic Studying Effort

Rank effects may affect student studying effort. This may be due to students' increasing their learning effort, since the marginal cost of effort may decrease in response to an increase in learning confidence, resilience, and perseverance (Murphy and Weinhardt, 2020). Or, alternatively, parents may incentivize their children to study more when they realise their child's high achievement rank.

To study rank effects on study effort, we construct a variable that captures student autonomic studying. To do so, we combine two items from the student questionnaire regarding the average weekly hours spent on extra schoolwork assigned by parents or cram school on weekdays and weekends and compute weekly total hours of studying to measure the extra studying and learning effort.[34] We then replace subsequent test scores with the newly constructed outcome variable in specification (2). Table 7 shows that students who end up having a higher rank spend more time on schoolwork weekly, on average. A 10-percentile increase in achievement rank (conditional on the baseline achievement) would lead to an increase in autonomic studying hours by 11% from the average (0.538/4.87). This translates into an additional half an hour of extra autonomic study per week.

7 Identifying the Mechanisms of Rank Effects

The results reported above show that rank effects have a significant impact on later outcomes. In this section, we explore the potential mechanisms through which students' rank in the classroom affects their academic achievement. As pointed out by Denning, Murphy, and Weinhardt (2021), rank effects may be driven by a reaction to the rank from any individual—for instance, students, parents, or teachers. In this section, we examine the possible channels using a rich set of behavioral outcomes based on responses to school questionnaires of students in the sample and their parents. We focus on three potential mechanisms: (1) students' beliefs, (2) parents' beliefs, and (3) teachers' investment. We are aware, of course, that we are not able to measure all relevant mechanisms, and we cannot rule out the possibility that other mechanisms are in place, but the analysis presented in this section provides important insights regarding possible mediating factors that drive the positive effect of ranks on students' achievements.

Our mechanism analysis consists of three parts. First, we explore the extent to which achievement rank affects each possible mechanism outcome. To do so, we replace the outcome variable in the main specification with each of the mechanism outcomes and report the estimated rank effects. Second, we focus on each related mechanism channel and quantify their mediation power on the rank effects. Lastly, we examine the extent to which each mechanism explains the nonlinear achievement rank effects.

To examine the impact of each mechanism to explain rank effects, we use specification (2) and replace the dependent variable with the q^{th} mechanism variable m, denoted as $m^q_{i,s,c}$:

$$m^q_{i,s,c} = \alpha^q + \beta^q rank^0_{i,s,c} + \sum_{s'}^{S} G(y^0_{i,s',c})[\mathbf{1}(s' = s)] + \boldsymbol{X}'_{i,s,c}\boldsymbol{\gamma}^q + \eta^q_c + \epsilon^q_{i,s,c} \quad q \in \{1, ..., Q\} \tag{5}$$

We obtain the estimated parameter β^q for each mechanism m^q, and report the corresponding standard error in Table 8.

[34] We use the student survey question: "How much time on average did you spend on extra schoolwork in weekdays and on weekends" to compute students' total hours spent on extra schoolwork in the week.

7.1 Student Beliefs

To examine how students' self-belief changes in response to their achievement ranks, we focus on (a) students' self-perception in achievement rank, captured by the survey question "How does your academic record rank in your class at present?" and (b) students' core subject learning confidence, captured by two sets of survey questions: (1) "How difficult is mathematics/Chinese/English for you at present?" and (2) "How much do you agree that mathematics/Chinese/English helps with your future."[35] Students perceive themselves as ranking around the 55$^{\text{th}}$ percentile in the class, on average, as shown in Table A.5. We use specification (5) and estimate the impact of achievement rank on student self-perception in rank conditional on student baseline achievement and other controls. Panel A of Table 8 shows that students with a higher achievement rank have a significantly higher self-perception in class rank. For example, a 10-percentile increase in achievement rank in class (equivalent to around 5 rank positions for the average class size of 45 students) would increase students' self-perception in rank by 1.8 percentiles (around 1 rank position for the average class size of 45 students), conditional on the baseline achievement and other controls. In addition, we find that a higher achievement rank would raise students' core subject learning confidence. These findings are in line with the rank effects literature (Carneiro et al., 2022; Elsner and Isphording, 2017; Murphy and Weinhardt, 2020; Pagani et al., 2021) and psychological literature (Marsh, 1987; Marsh et al., 2007), which suggest that students update their perceived ability and beliefs about their strengths and weaknesses based on their local rank position.[36]

7.2 Parental Beliefs

Recent evidence shows that parents may adjust their investments in response to their children's performance (Cobb-Clark et al., 2021; Dizon-Ross, 2019; Murphy and Weinhardt, 2020; Pagani et al., 2021). While the previous literature focuses on parental investments in time and financial investment, the evidence on how parents update their beliefs after learning their child's achievement rank in the class is limited. This is not surprising, given that parents are unaware of their child's rank in most settings.

Our analysis of parental beliefs is based on the following items: (1) parents' perception of child's achievement rank, captured by the item "How does this child's academic record rank in his/her class at present?"; (2) parents' requirements for child's study, captured by the item "What are your requirements for this child's academic record?"; (3) an indicator variable for whether parents have high expectations for their child's education level, captured by the item "What is the highest level of education do you expect this child to receive?"; and (4) an indicator variable for whether parents have

[35] Details on how we construct student self-erception in ranks can be found in Appendix Table A.1.

[36] Rank effects may be associated with perceived ability (Marsh, 1987; Marsh et al., 2007). Students may have imperfect knowledge about their own ability (Azmat et al., 2019; Bobba and Frisancho, 2016; Goulas and Megalokonomou, 2021; Stinebrickner and Stinebrickner, 2012). They may infer their relative ability from information or realization of their relative performance to form expectations about their perceived ability.

high expectations for their child's career prospects, captured by the item "What kind of job do you most expect this child to do in the future?". We explain how we construct those variables in Appendix Table A.1 and provide the original survey questions in Appendix D.[37]

The estimates in Panel B of Table 8 suggest that a higher achievement rank in a class significantly increases parental perception of their child's rank and imposes more demanding requirements for parents with respect to their child's achievement rank in the later period. If a student's rank in the class moves from the bottom to the top (conditional on their baseline achievement), that would increase parental beliefs about their child's rank and expectations for their child's class rank in the subsequent period by 21.7 (0.116/0.533) percentiles and 23.6 (0.173/0.733) percentiles from the average, respectively. Additionally, parents' expectations for their child's educational level and career prospects increase with their child's rank. A 10-percentile increase in a child's rank (equivalent to around 5 rank positions for the average class size of 45 students) would make parents 2.7 and 3.6 percentage points more likely to believe that their children will achieve a high level of education and a promising career path, respectively.

This effect is evident in each of the four items and is precise for all items. Overall, these results suggest that academic gains due to a higher rank are associated with changes in parental beliefs about their child's higher rank, stricter study requirements, and higher expectations for the child's attainments and career prospects.

7.3 Teachers' Investment

Teachers' behaviors in the classroom and decisions about time allocation across students may depend on students' relative academic achievement. Teachers may not be able to treat all students equally, but instead provide more support for students who have a higher rank (Pop-Eleches and Urquiola, 2013). We test this hypothesis by using CEPS student responses to the questionnaire about subject teachers' and head teachers' actions in the classroom.

We use four items to examine the impact of a student's being assigned a higher rank on the relationships between students and teachers. The first item identifies whether a student believes that their subject teacher always pays attention to them in the class (this is captured by three items on the student questionnaire: "My mathematics/Chinese/English teacher always pays attention to me").[38]

[37] Table A.5 shows that the average parental perception of their children's rank is in the 53$^{\text{th}}$ percentile and they would expect their child to rank at around the 73$^{\text{th}}$ percentile, which is above the class average. In addition, 28% of parents have high expectations for their children's educational level, and 55% of parents have high expectations for their children's career prospects.

[38] We first transform students' response to each subject teacher's behavior into a binary variable of value 1 if the student strongly agrees with the statement. Table A.5 shows that 21% (20% and 23%) of students believe that Chinese (math and English) teachers always pay attention to them. We then aggregate students' responses for each subject at student level by using principal component analysis (PCA). Details on how we construct the related variables can be found in Table A.1.

The second item identifies whether the subject teacher always praises the student in the class (this is captured by three items on the student questionnaire: "My mathematics/Chinese/English teacher always praises me"). The third item identifies whether the subject teacher always asks the student questions in the classroom (this is captured by three items on the questionnaire: "My mathematics/Chinese/English teacher always asks me to answer questions in class").[39] The last item identifies whether the head teacher always praises the student (this is captured by one item on the student questionnaire: "My homeroom teacher always praises me").[40]

The effects of ranks on these variables are shown in Panel C in Table 8. All estimates are imprecise, which indicates that teachers are not perceived as adjusting their behavior to student ranks. Overall, we find that teachers most likely do not react to student ranks, which is consistent with existing evidence (Elsner and Isphording, 2017; Murphy and Weinhardt, 2020).

7.4 Mediation Analysis

The mechanisms discussed above clearly show that rank effects may be driven by changes in (1) students' beliefs, and (2) parents' beliefs. In this section, we use a mediation analysis to identify the extent to which each channel contributes to explaining rank effects and their combined explanatory power, following the spirit of Heckman, Pinto, and Savelyev (2013) and Gelbach (2016).

We use specification (2) and augment it with all mechanism variables:

$$y^1_{i,s,c} = \alpha' + \beta' rank^0_{i,s,c} + \sum_{q=1}^{Q} \lambda^q m^q_{i,s,c} + \sum_{s'}^{S} G(y^0_{i,s',c})[\mathbf{1}(s' = s)] + \boldsymbol{X}'_{i,s,c}\boldsymbol{\gamma} + \eta_c + \epsilon^1_{i,s,c} \tag{6}$$

By estimating (6), we obtain the estimated parameters for achievement rank (β') and the mechanism variables (λ^q), and we then derive the following decomposition equation:[41]

$$\hat{\beta} = \hat{\beta}' + \sum_{q=1}^{Q} \hat{\lambda}^q \hat{\beta}^q \tag{7}$$

We interpret this equation as follows: $\hat{\beta}$ is the baseline estimate of the overall rank effects from the reduced form equation (2). The mediation power of a mechanism component $m^q_{i,s,c}$ for explaining the rank effect is pinned down by the corresponding term $\hat{\lambda}^q \hat{\beta}^q$. The combined explanatory power of all mechanisms is therefore $\sum_{q=1}^{Q} \hat{\lambda}^q \hat{\beta}^q$. The remaining portion of the rank effect unexplained by

[39]The same as for the first item, we use the PCA aggregation approach for student's responses to questions about the subject teacher's question and praise behaviors.

[40]We construct a binary indicator of value 1 if the student strongly agrees with this statement.

[41]We recognize that the derivation of equation (7) relies on a relatively strong assumption that the coefficients in equation (6) are consistently estimated. This could be violated if the observed mechanisms are correlated with unobserved variables captured by the error term. That would cause the rank estimates β^q to be biased. Therefore, we only interpret our decomposition results as a useful approximation of the relative importance of mediators. We show the derivation of equation (7) in Appendix C.

the proposed mechanisms is captured by $\hat{\beta}'$. We normalize the explanatory power of each mechanism component to the share of the overall rank effects, $\hat{\lambda}^q\hat{\beta}^q/\hat{\beta}$, which provides us with an interpretation of its relative importance in explaining the rank effects.

Table 9 reports the change in the estimated rank effects $\hat{\beta}'$ when we gradually add the mechanism variables in specification (6). Column 1 just replicates the baseline rank effect, in which none of the mechanism variables are included. In column 2, we replicate column 1 using a reduced sample for which we have all responses for the mechanism variables in the student and parents survey. The estimated rank effect (0.487) remains robust compared with the main estimate.[42] Column 3 shows that the estimated rank effect drops significantly (from 0.487, se= 0.218 to 0.259, se= 0.218) when we include controls for students' self-belief and parents' beliefs. This implies that the increase in student test scores as a response to ranks may be caused by students' updated self-beliefs or their parents' updated beliefs about their child's rank and attainment. These findings suggest that these two channels, though not exhaustive, are the primary drivers through which the estimated rank effects operate.

Table 10 shows the relative explanatory power of each channel in explaining the estimated rank effects based on equation (7). Our mediation analysis shows that changes in students' beliefs and parental beliefs are equally important for explaining rank effects, with 23.2% of the estimated rank effect explained by the former and 23.6% explained by the latter.

7.5 Mechanisms Behind Nonlinear Rank Effects

We further investigate the mechanisms behind the nonlinear rank effects explored in Section 4.2. To do so, we adopt a parsimonious version of specification (4) by splitting rank into 10 deciles.[43] We replace the outcome variable with each mechanism variable discussed above. Table 11 shows the estimated effects while the outcome is each mechanism variable (listed horizontally). We vertically present the estimated rank effects for each one of the ten deciles. *Rank Decile 1* denotes students in the 1^{st} decile of the achievement rank distribution (near the bottom of the class); *Rank Decile 10* denotes students in the 10^{th} decile of the achievement rank distribution (near the top of the class). The 5^{th} decile is omitted as a point of comparison. Self-perception and learning confidence are increasing with relative performance (columns 1 and 2). Students near the bottom (Rank Deciles 1 and 2) have lower self-perception of their actual achievement rank and confidence in learning core subjects , while students above the median have a higher self-perceived rank and confidence in learning (compared with those ranked at the median).

[42] We check whether the likelihood of a student or a parent skipping a survey question is correlated with student achievement rank. To do so, we construct a binary indicator that takes the value of 1 if the response is missing and 0 otherwise. We then replace the outcome variable in (2) with the binary variable for a missing response. Table A.6 shows very small and statistically insignificant estimated effects. This indicates that there is no association between a student's achievement rank and the probability of a student or a parent not responding a question in the survey.

[43] We use the 5^{th} decile as the reference group to approximate those who rank at the median.

Columns 3-6 show that parental beliefs are also increasing with relative performance. In particular, parents whose children have a lower achievement rank would also have a lower perception of their child's rank and would be less likely to believe that their child will obtain a promising education level and career, compared with parents whose children rank at the median. However, when the child ranks below the median, parents are not found to give up on their child's learning, which is indicated by the small estimates (relative to the standard errors) in column 4 for those ranking from deciles 1-4 (compared with decile 5) in the class.

Overall, the pattern in Table 11 suggests that the academic gains from having a higher achievement rank are likely driven by the positive beliefs and perceptions of both students and parents. However, the loss in subsequent test scores from having a lower achievement rank is more likely to be the result of a pessimistic belief by students about themselves rather than a change in their parents' beliefs.

8 Conclusion

We study a setting in which ranks are salient (by students and teachers) and students are quasi-randomly assigned to classrooms within schools. Students with the same baseline test scores end up having different achievement ranks in their assigned classroom due to small changes in the dispersion of the classroom test scores distribution. We view our main contributions as twofold: first, we exploit an educational system that is highly competitive and thus, relative student achievement is explicitly communicated. We provide evidence that students are well aware of their objective achievement rank, and so are their parents. The existing literature assumes that students are aware of their rankings, but, in practice students are very rarely provided with this information. Second, by means of a unique survey on student and parents perceptions, we explore who is driving the estimated rank effects. This is particularly relevant in settings in which ranks are salient to all involved participants. Parents are more likely to respond to their child's rank when they are aware of it.

We find that a student who is randomly assigned to a classroom in which they end up having a higher achievement rank performs better in the later period, conditional on baseline test scores. In particular, a 1-standard-deviation increase in achievement rank increases subsequent test scores by 6% of a standard deviation. The effects are more pronounced for male and overconfident students. We also find that higher ranked students end up spending more hours on autonomic studying. Rank effects show a nonlinear pattern, with significant losses for bottom-ranked students and more gains for top-ranked students.

Using rich data on the performance and behavioral outcomes of middle school students and their parents and teachers in China, we are able to examine the mechanisms through which these rank effects may affect students' performance. We disentangle three channels through which these mechanisms may affect students: (1) one that operates through a change in student self-perception about their own rank, (2) a second that reflects changes in parental beliefs, and (3) a third that reflects changes in teachers' behavior in the classroom. An exploration of those mechanisms shows that not only (1), but also

(2) explain student academic gains. The effects on improved performance due to higher ranks do not appear to come through (3). We conduct a mediation analysis and identify the relative weight of each mechanism. However, we do not rule out the possibility that other mechanisms may be in play. We show that changes in individual and parental beliefs make an equal contribution to explaining rank effects, and together they explain around 47% of rank effects. Our results provide important insights into the channels through which peers compare with each other and influence student learning.

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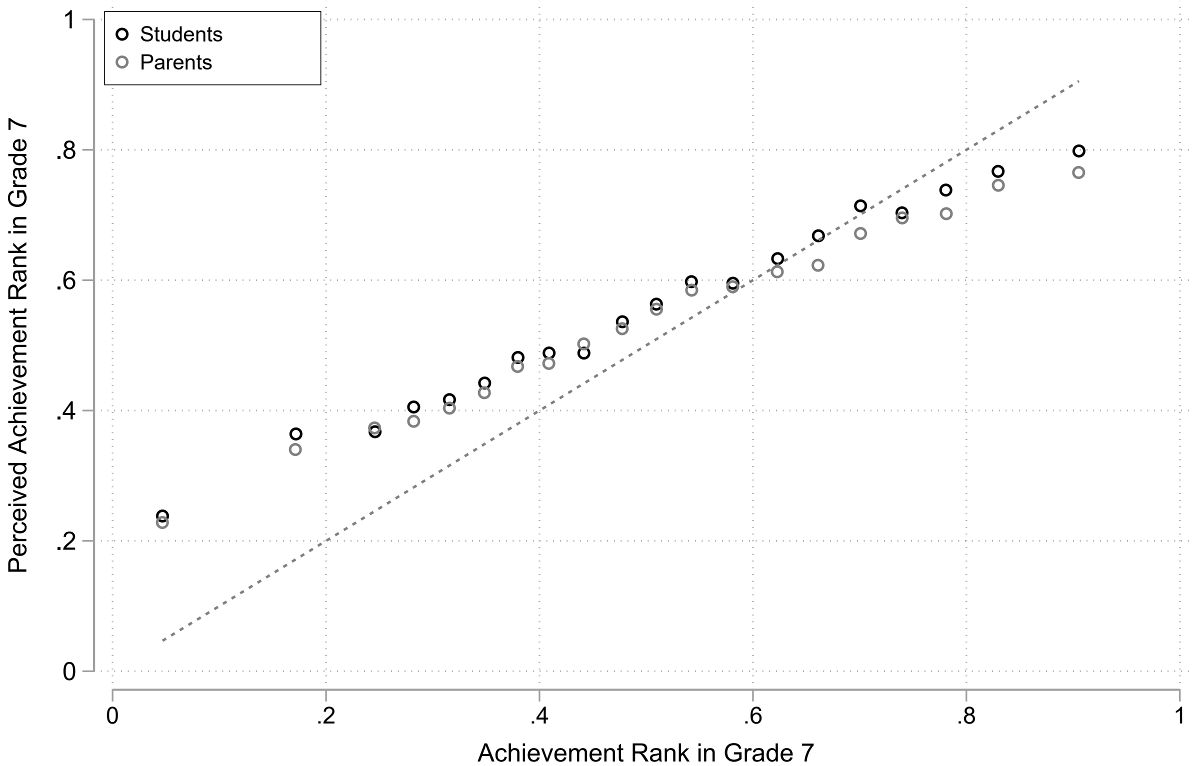
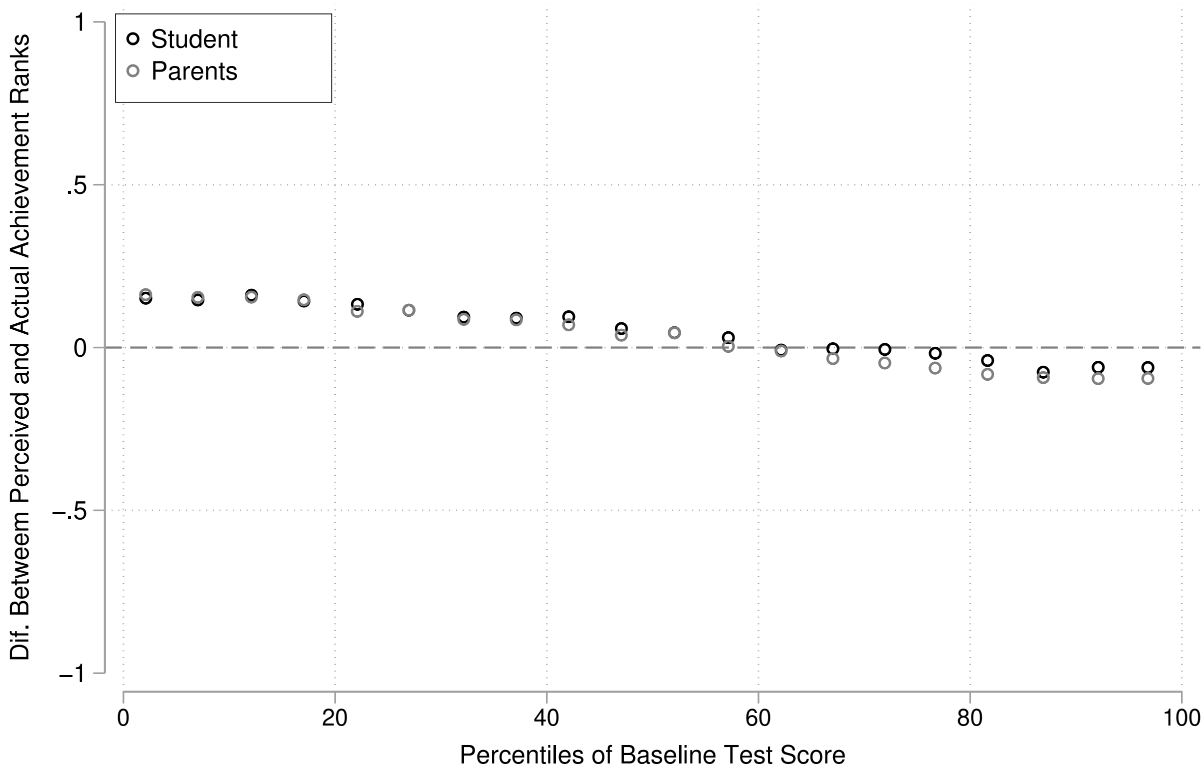
Figure 1: The Relationship Between Perceptions of Ranks and Student Objective Ranks



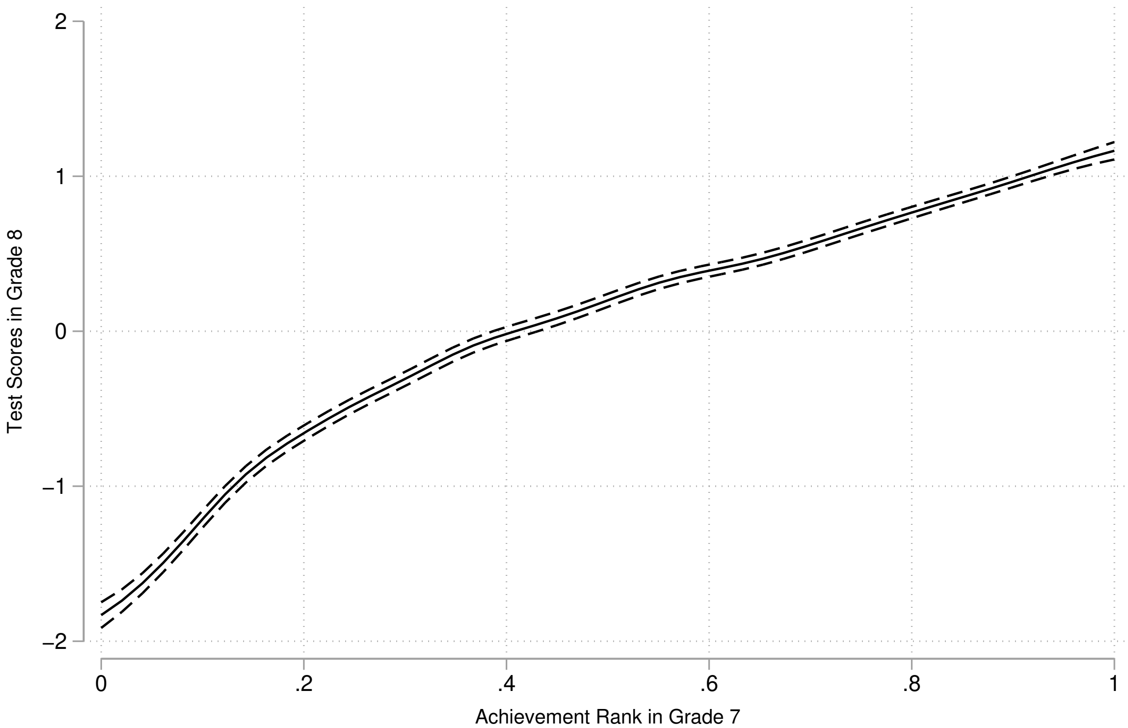
Notes: This figure shows two binned scatter plots that demonstrate 1) the relationship between students' self-perception of their achievement rank and their objective achievement rank in grade 7 (in black) and 2) the relationship between parents' perception of their child's achievement rank and students' objective achievement rank in grade 7 (in gray). Both plots are drawn conditional on student baseline test scores.

Figure 2: Difference Between Perceived and Objective Achievement Ranks by Ability



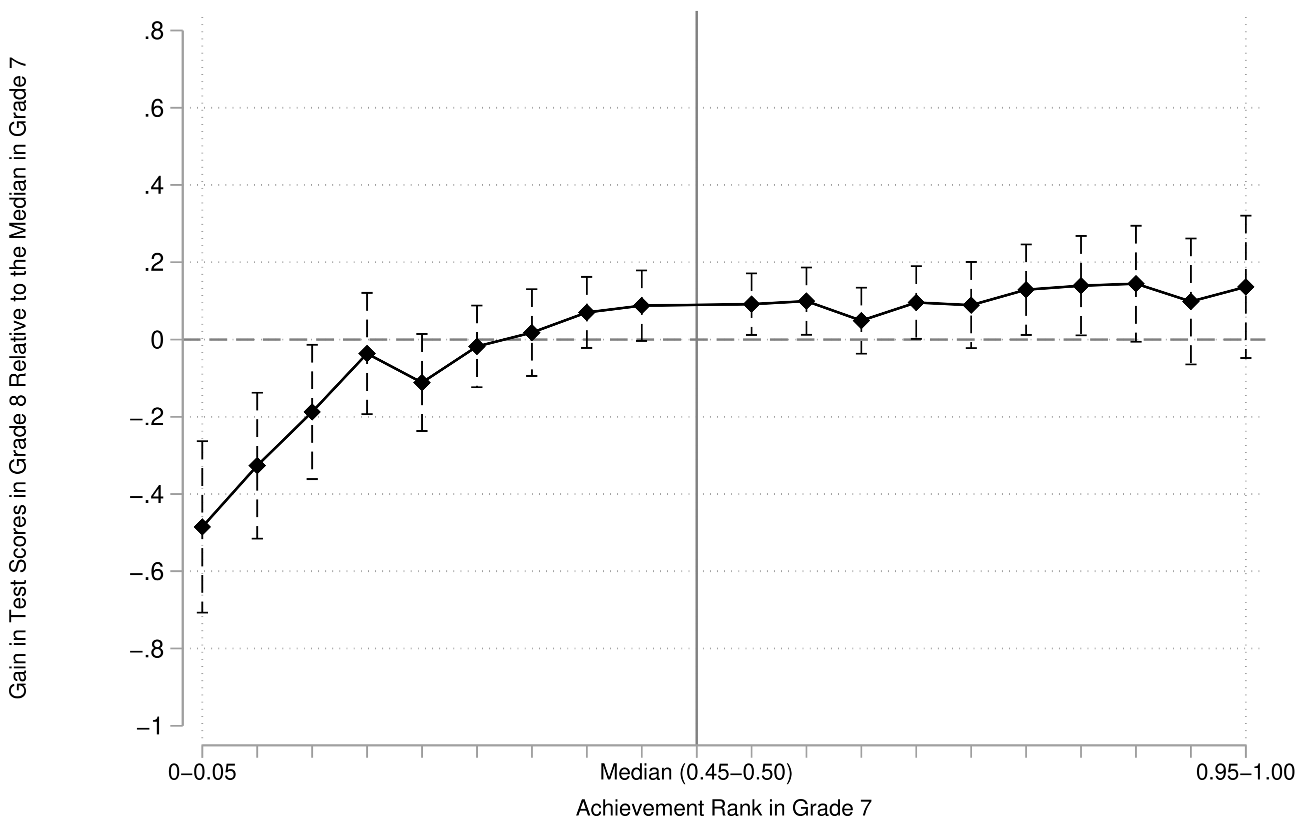
Notes: This figure shows two binned scatter plots that demonstrate the difference between perceptions of achievement ranks (by students and their parents) and students' objective achievement ranks for each percentile of students' baseline test scores. The black scatter plot shows the difference in students' self-perception of their achievement rank and their objective achievement rank in grade 7 for each percentile of baseline test scores. The gray scatter plot presents the difference between parents' perception of their child's achievement rank and their child's objective achievement rank in grade 7 for each percentile of baseline test score.

Figure 3: THE RELATIONSHIP BETWEEN STUDENT ACHIEVEMENT RANK IN GRADE 7 AND SUBSEQUENT STUDENT TEST SCORES IN GRADE 8



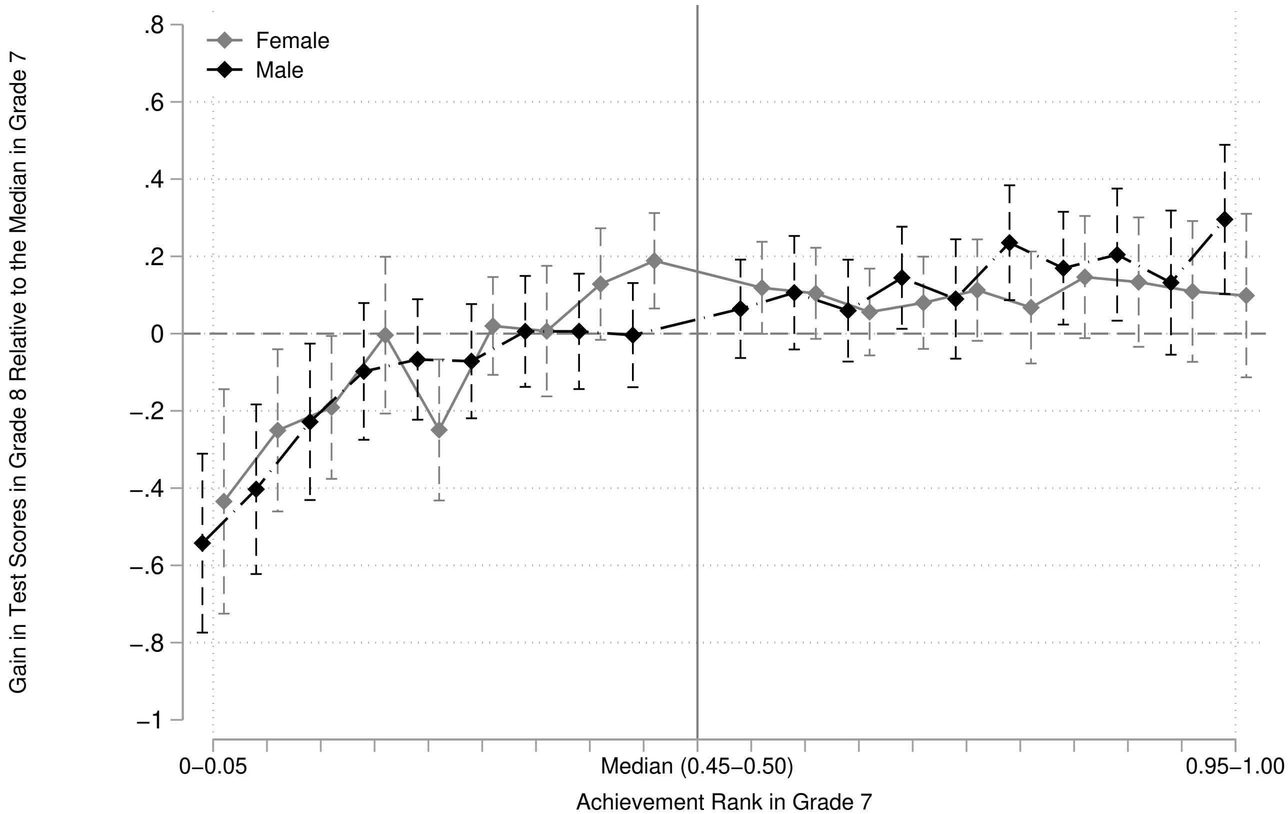
Notes: This figure plots the relationship between the student achievement rank in their class in grade 7 and (standardized) student test scores in grade 8 using a nonparametric local polynomial smoothing line and the corresponding 95% confidence interval.

Figure 4: Nonlinear Rank Effects (Relative to the Median)



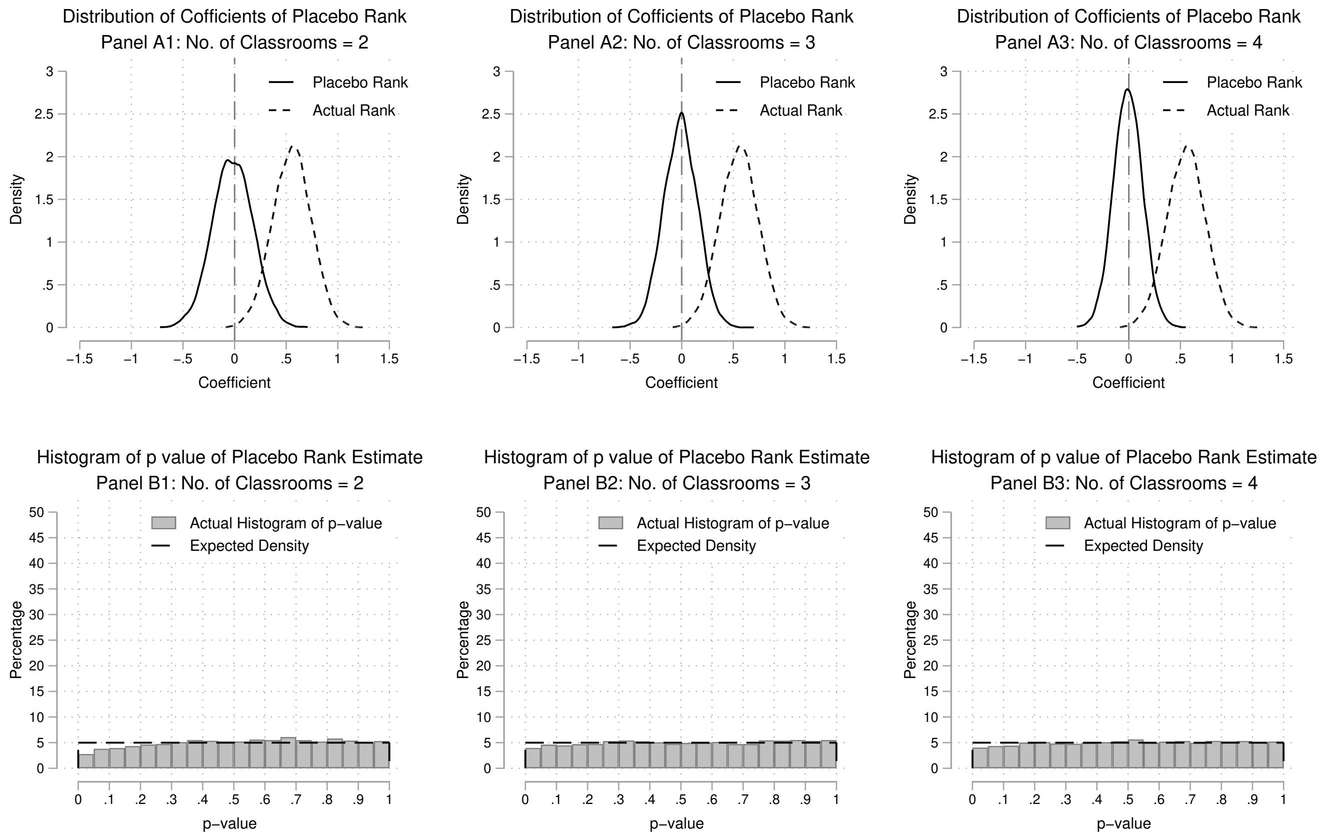
Notes: The figure plots the estimated parameters ρ_r and the corresponding 90% confidence intervals (calculated using standard errors clustered at classroom level) from the estimation of specification (4). The left-out category is students with ranks in the $45^{\text{th}} - 50^{\text{th}}$ percentiles or 10^{th} ventile (represented by the vertical line).

Figure 5: Nonlinear Rank Effects by Gender (Relative to the Median)



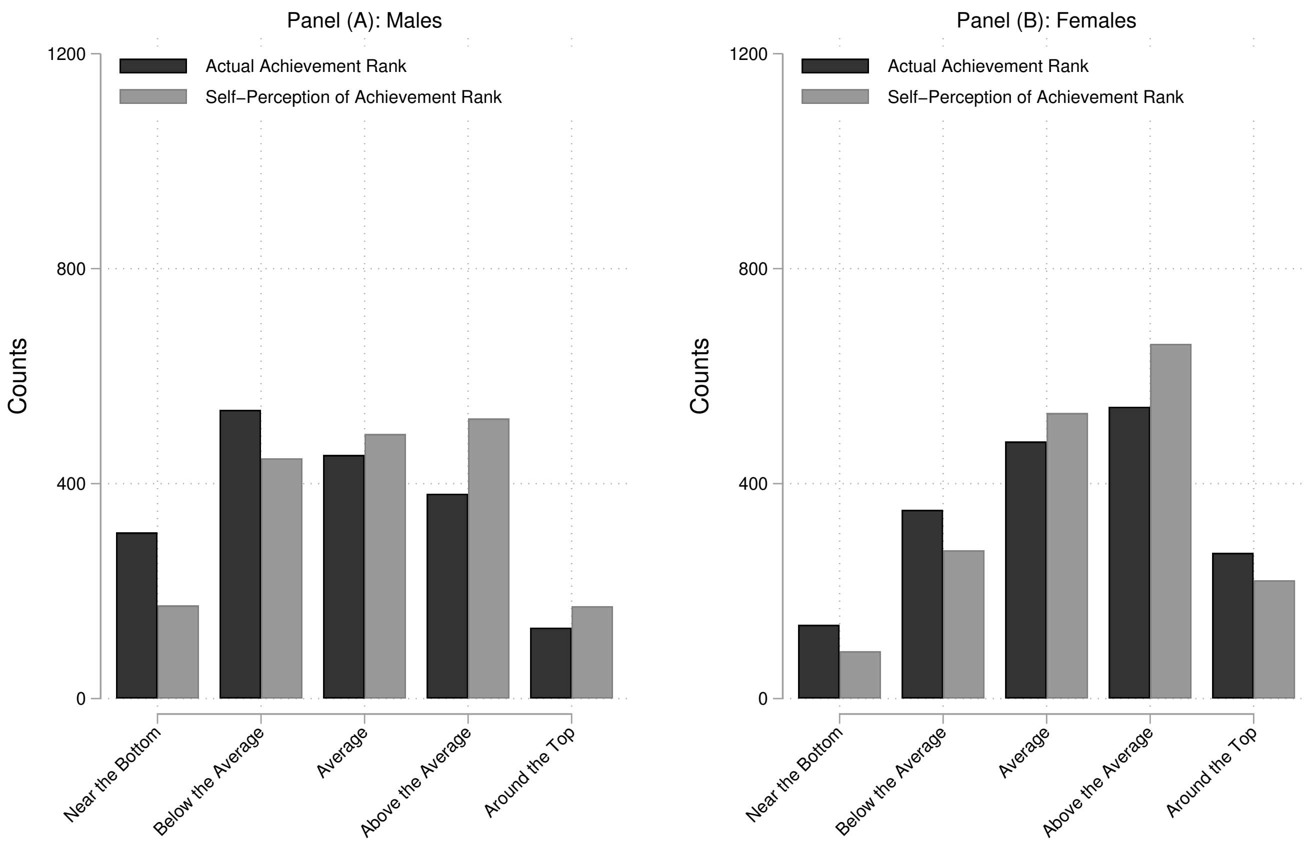
Notes: The figure plots the nonlinear rank effects of males relative to the median (in black) and that of females (in gray) relative to the median, as well as their corresponding 90% confidence intervals (calculated using standard errors clustered at classroom level). The left-out category consists of those ranking around the median—the 10^{th} ventile (i.e., $45^{\text{th}} - 50^{\text{th}}$ percentiles), represented by the vertical line.

Figure 6: Monte Carlo Simulations and Placebo Ranks



Notes: The figure plots the effect of placebo rank (solid curve) in Panels A1-A3 and the corresponding p-value in Panels B1-B3 from 10,000 estimations. For comparison, Panels A1-A3 also show the distribution of the actual rank effect (dotted curve) using the baseline estimate and standard error from the OLS estimation of specification (2). This clearly shows a positive rank effect. To construct the placebo rank, we remix an individual's classmates by carrying out random reassignment of each student to a false group of classmates. We use the existing students in each school, but only reshuffle them across classroom numbers. Each time, we compute the achievement rank of students from their falsely generated group of classmates and estimate equation (2) to obtain placebo rank effect estimates and corresponding p-values. We repeat this process for 10,000 times to obtain the distribution of estimates and p-values. In the left panels (Panel A1 and B1), each school contains only 2 classrooms. We remix classmate composition across 2 classrooms within the same school and perform the aforementioned exercise, with results shown in Panels A1 and B1. We also create one more and two more hypothetical classrooms, remix the classmate composition, and perform the same exercises in Panels A2 and B2 (3 classrooms), as well as Panels A3 and B3 (4 classrooms).

Figure 7: Histograms of Actual and Perceived (by Students) Ranks by Student Gender



Notes: The figure shows the distributions of students' actual achievement (in black) and self-perceived (in gray) ranks by student gender. Panel (A) presents the distributions of both ranks for males and panel (B) for females. The data on self-perception of ranks are obtained from the questionnaire. To classify student achievement rank, we label students with a rank of 0-0.125 "Near the Bottom"; 0.125-0.375 "Below the Average"; 0.375-0.625; "Average"; 0.625-0.875 "Above the Average"; and 0.875-1 "Around the Top."

Table 1: Descriptive Statistics of Study Sample

	Mean	**Std. Dev.**	**Min.**	**Max.**	**N**
Student Characteristics					
Age	13.436	0.633	12	17	3592
Female (1=Yes)	0.496	0.500	0	1	3592
Minority (1=Yes)	0.074	0.262	0	1	3592
Only Child in Family (1=Yes)	0.567	0.496	0	1	3592
Attend Kindergarten (1=Yes)	0.859	0.349	0	1	3592
Skip Grade in Primary School (1=Yes)	0.011	0.105	0	1	3592
Repeat Grade in Primary School (1=Yes)	0.080	0.272	0	1	3592
Family Characteristics					
Rural Residence (1=Yes)	0.418	0.493	0	1	3592
Local Residence (1=Yes)	0.787	0.410	0	1	3592
High Income (1=Yes)	0.078	0.268	0	1	3592
Father's Years of Schooling	11.080	3.246	0	18	3592
Mother's Years of Schooling	10.561	3.430	0	18	3592
Regressor of Interest					
Achievement Rank (Grade 7)	0.499	0.285	0	1	3592
Middle School Test Scores					
Test Score in 7th Grade	247.517	62.466	30	413	3592
Test Score in 8th Grade	243.176	73.063	0	440	3592
Other Statistics					
School Size	90.326	24.761	51	142	46
Public School (Yes=1)	0.891	0.315	0	1	46
Classroom Size	45.163	12.615	15	77	92

Notes: Our study sample includes students in middle schools in China. These schools implement a random assignment of students to classrooms and are included in both waves of CEPS that we describe in the text (Section 2.2). *Minority* takes the value of 1 if the ethnic group is not Han Chinese. 55 ethnic groups contribute to the minority ethnic group.

Table 2: Balancing Tests for Achievement Rank, Classroom Identifiers, and Classmates' Ability

	Achievement Rank	**1**(Classroom number=2)	Peers Ability Std.
Dependent Variables:	(1)	(2)	(3)
Student Characteristics			
Age	-0.258	0.022	0.003
	(0.197)	(0.029)	(0.002)
Female (1=Yes)	-0.241	0.001	0.001
	(0.148)	(0.014)	(0.001)
Minority (1=Yes)	-0.019	0.005	-0.000
	(0.065)	(0.009)	(0.001)
Only Child in Family (1=Yes)	0.006	0.002	-0.002
	(0.164)	(0.023)	(0.002)
Attend Kindergarten (1=Yes)	0.186	0.007	-0.001
	(0.116)	(0.022)	(0.002)
Skip Grade in Primary School (1=Yes)	0.030	0.006	0.000
	(0.029)	(0.006)	(0.000)
Repeat Grade in Primary School (1=Yes)	-0.129	-0.004	0.002
	(0.083)	(0.014)	(0.002)
Family Characteristics			
Rural Residence (1=Yes)	0.389	0.003	0.002
	(0.159)**	(0.026)	(0.002)
Local Residence (1=Yes)	-0.340	0.004	-0.000
	(0.142)**	(0.036)	(0.001)
High Income (1=Yes)	-0.066	0.006	-0.000
	(0.095)	(0.016)	(0.001)
Father's Years of Schooling	-1.427	-0.027	-0.007
	(1.113)	(0.159)	(0.013)
Mother's Years of Schooling	-1.858	-0.137	-0.017
	(1.030)*	(0.184)	(0.012)
Quartic in 7^{th} Grade Test Scores by School	✓	✓	✓
Classroom FE	✓	✗	✓
School FE	✗	✓	✗

Notes: Column 1 shows estimates of the achievement rank in 7^{th} grade from regressions that regress each student's predetermined characteristics and family characteristics on the achievement rank in 7^{th} grade, conditional on classroom fixed effects. Column 2 shows estimates of the classroom indicator from regressions that regress each classroom-level mean of student characteristics and family characteristics on the classroom indicator, conditional on school fixed effects. In column 2, the unit of observation is the unique classroom and the estimation sample size is the number of unique classrooms, 92. Column 3 shows estimates of the standard deviation (self-excluded) of classmates' ability from regressions that regress each student's characteristics and family characteristics on the standard deviation (self-excluded) of classmates' ability, conditional on classroom fixed effects. All regressions additionally control for the 4^{th}-order polynomial function of 7^{th} grade test scores by school fixed effects. *, **,*** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in the parentheses in columns 1 and 3 are clustered at classroom level; the robust standard errors reported in parentheses in column 2 are clustered at school level.

Table 3: ACHIEVEMENT RANK EFFECTS ON SUBSEQUENT TEST SCORES

Dependent Variables:	Test Scores in 8th Grade (Standardized)	
	(1)	(2)
Achievement Rank (Grade 7)	0.557***	0.557***
	(0.185)	(0.186)
N	3,592	3,592
Adjusted R^2	0.752	0.753
Quartic in 7^{th} Grade Test Scores by School	✓	✓
Student Characteristics	✗	✓
Family Characteristics	✗	✓
Classroom FE	✓	✓

Notes: The table presents the estimated effect of achievement rank in grade 7 on students' test scores in grade 8. The dependent variable is the standardized test score in the 8^{th} grade. Subsequent test scores in 8^{th} grade are standardized to a distribution with zero mean and a unit standard deviation within the class. Specification (2) produces the estimate in column (1) with controls for classroom fixed effects, 4^{th}-order polynomial of a student's test score in 7^{th} grade, but without controls for student and family characteristics. Column 2 includes controls for student characteristics and family characteristics on top of existing controls included in column (1). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

Table 4: Heterogeneous Achievement Ranks by Student Characteristics

	(1) By Gender	(2) By Family Income Level	(3) By Minority Group	(4) Father's Years of Schooling	(5) Mother's Years of Schooling
Achievement Rank	0.663***	0.545***	0.559***	0.520**	0.662***
	(0.185)	(0.185)	(0.188)	(0.227)	(0.222)
Female × Achievement Rank	-0.204**				
	(0.078)				
Female (1=Yes)	0.185***				
	(0.049)				
High Income × Achievement Rank		0.146			
		(0.096)			
High Income (1=Yes)		-0.095			
		(0.069)			
Minority × Achievement Rank			-0.039		
			(0.149)		
Minority (1=Yes)			-0.035		
			(0.095)		
Father's Years in Schooling × Achievement Rank				0.003	
				(0.012)	
Father's Years of Schooling				-0.000	
				(0.007)	
Mother's Years in Schooling × Achievement Rank					-0.010
					(0.011)
Mother's Years of Schooling					0.008
					(0.008)
N	3,592	3,592	3,592	3,592	3,592
Adjusted R^2	0.754	0.753	0.753	0.753	0.753
Quartic in 7th Grade Test Scores by School	✓	✓	✓	✓	✓
Student and Family Characteristics	✓	✓	✓	✓	✓
Classroom FE	✓	✓	✓	✓	✓

Notes: We add interaction terms between achievement rank and female indicator, family income level indicator, minority indicator, father's years of schooling, and mother's years of schooling in specification (2) separately, and show the estimated effects for the interaction and individual terms of the interaction in each column. All specifications control for other student characteristics and family characteristics (apart from those shown in the table), and the quartic polynomial functional forms of students' 7th grade test score interacted with school indicators. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

Table 5: Heterogeneous Achievement Ranks by Student Confidence

	(1) Self-perceived Achievement Rank > Objective Achievement Rank	(2) Self-perceived Achievement Rank < Objective Achievement Rank
Achievement Rank	0.977***	0.524
	(0.293)	(0.355)
N	2,221	1,371
Adjusted R^2	0.766	0.765
Quartic in 7th Grade Test Scores by School	✓	✓
Student Characteristics	✓	✓
Family Characteristics	✓	✓
Classroom FE	✓	✓

Notes: The table presents the estimated rank effects on student subsequent test scores for students who over and under perceive their relative achievement in the class, separately. Students over perceive their achievement rank if their self-perceived rank is larger than their objective achievement rank early in grade 7. Students under perceive their achievement rank if their self perceived rank is smaller than their objective achievement rank. The outcome variable is the standardized test scores in the 8th grade. The estimated effects in column (1) are generated by estimating the main specification (2) for students whose self-perceived achievement rank is larger than their objective achievement rank in semester 1 of grade 7. The estimated effects in column (2) are generated by estimating the main specification (2) for students whose self-perceived achievement rank is smaller than their objective achievement rank in semester 1 of grade 7. These regressions control for classroom fixed effects, 4th-order polynomial of a student's baseline test scores in grade 7, student characteristics, and family characteristics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

Table 6: Achievement Rank Effects on Test Scores, While Adding Controls

		Dependent Variable: Test Scores in 8th Grade
Regressor of Interest: Achievement Rank		
(1)	Baseline Estimates	0.557
		(0.186)***
(2)	Control for Self-Report Motivation	0.597
		(0.174)***
(3)	Control for Mean and Standard Deviation of Peers' Achievement	0.531
		(0.181)***
(4)	Control for Nonlinear Peer Effects	0.476
		(0.206)***
Alternative Definition of Rank		
(5)	Subject Rank Effect (Conditional on Individual FE)	0.470
		(0.000)***
Flexible Function Form of Test Scores		
(6)	Linear	0.349
		(0.134)**
(7)	Quadratic	0.222
		(0.166)
(8)	Cubic	0.352
		(0.172)**
(9)	Quartic	0.557
		(0.186)***
(10)	Quintic	0.677
		(0.183)***
(11)	Sextic	0.617
		(0.178)***

Notes: This table presents the results of a series of robustness checks. Each row displays the estimated effects for achievement rank obtained from separate regressions. Row 1 reports baseline estimates. Row 2 shows results obtained from the main specification that also controls for a student *motivation measure*. Row 3 shows results from the main specification that also controls for the class-level leave-out mean and standard deviation of peers' achievement. Row 4 shows results from the main specification that also controls for nonlinear peer effects by including student type (high-, middle-, and low-achieved types based on whether their baseline test scores in Grade 7 are in the top, middle, or bottom third of the baseline test score distribution in the classroom, respectively.), composition of each type, and the interaction between them in the model (following the approach of Zolitz and Feld (2017)). Row 5 stacks students by the 3 core subjects and estimates the subject-specific rank effect by conditioning on student fixed effects and classroom-by-subject fixed effects. Rows 6-11 show the results from regressions that use the increasing order of polynomial functional forms of students' 7^{th} grade test score interacted with school indicators. All specifications control for student and family characteristics. Specifications in rows 1-5 and row 9 control for the 4^{th}-order polynomial functional forms of students' 7^{th} grade baseline test score interacted with school indicators. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

Table 7: Achievement Rank Effects on Autonomic Studying Effort

Dependent Variable	Coefficient (1)	Standard Error (2)	N (3)
Hours in Autonomic Studying	5.380***	2.079	3520
Quartic in 7th Grade Test Scores by School	✓	.	.
Student Characteristics	✓	.	.
Family Characteristics	✓	.	.
Classroom FE	✓	.	.

Notes: This table presents the estimated achievement rank effects on hours in autonomic studying. The mean of hours in autonomic studying is 4.87 per week (sd=6.294). The regression includes a quartic polynomial of school-specific baseline achievement, student characteristics, family characteristics, and classroom fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

Table 8: Mechanisms Behind Achievement Rank Effects

	Coefficient	Standard Error	N
Dependent Variable	(1)	(2)	(3)
Panel A *Channel 1: Self Belief*			
Self-perception in Achievement Rank	0.178***	0.066	3580
Core Subjects Learning Confidence	0.783*	0.440	3544
Panel B *Channel 2: Parents' Belief*			
Parents' Perception of Child's Achievement Rank	0.116*	0.065	3577
Parents' Requirements for Child's Study	0.173*	0.101	3494
$\mathbf{1}$(High Expectations for Child's Educational Level)	0.268*	0.151	3505
$\mathbf{1}$(High Expectations for Child's Career Prospect)	0.355*	0.187	3523
Panel C *Channel 3: Teachers' Investment*			
Subject Teachers' Attention	0.108	0.357	3537
Subject Teachers' Praise	-0.375	0.355	3529
Subject Teachers' Question	-0.080	0.326	3510
Head Teachers' Praise	-0.032	0.112	3533
Quartic in 7^{th} Grade Test Scores by School	✓	.	.
Student Characteristics	✓	.	.
Family Characteristics	✓	.	.
Classroom FE	✓	.	.

Notes: This table presents results from separate regressions of the outcomes listed in the first column on student achievement rank in the classroom. Columns 1, 2, and 3 present the estimated coefficients, the related standard errors, and the number of observations, respectively. All regressions include a quartic polynomial of school-specific baseline achievement, student characteristics, family characteristics, and classroom fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

Table 9: Indirect Rank Effects through Mechanism Channels

	Dep.Var: Test Scores in Grade 8		
	(1) Baseline	(2) Baseline (Reduced Sample)	(3) + Self-Belief + Parental-Belief Channel
Achievement Rank	0.557***	0.487**	0.259
	(0.186)	(0.218)	(0.218)
Self-perception in Achievement Rank			0.521***
			(0.070)
Core Subjects Learning Confidence			0.010
			(0.007)
Parents' Perception of Child's Achievement Rank			0.341***
			(0.068)
Parents' Requirements for Child's Study			0.230***
			(0.043)
1(High Expectations for Child's Educational Level)			0.092***
			(0.022)
1(High Expectations for Child's Career Prospect)			0.030*
			(0.017)
N	3,592	2,981	2,981
Adjusted R^2	0.753	0.753	0.796
Quartic in 7^{th} Grade Test Scores by School	✓	✓	✓
Student Characteristics	✓	✓	✓
Family Characteristics	✓	✓	✓
Classroom FE	✓	✓	✓

Notes: Column (1) presents the baseline estimated rank effect. Column (2) replicates this estimation using a reduced sample, in which there are no missing values in any of the mechanism variables. Column (3) uses the baseline specification (2) and includes controls for student self-belief and parents' belief. We list those estimated effects for each of those variables vertically. All regressions include controls for student characteristics, family characteristics, the quartic polynomial functional forms of students' 7^{th} grade test score, and classroom fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

Table 10: The Relative Importance of Mediating Factors

Credible Mechanisms	% of Rank Effect Mediated	Cumulative % of Rank Effect Mediated
Channel 1: Self-Belief		
Self-perception in Achievement Rank	21.16	21.16
Core Subjects Learning Confidence	2.00	23.16
Channel 2: Parental-Belief		
Parents' Perception of Child's Achievement Rank	8.31	31.48
Parents' Requirements for Child's Study	8.33	39.81
1(High Expectations for Child's Educational Level)	4.15	43.96
1(High Expectations for Child's Career Prospects)	2.84	46.80

Notes: This table shows the decomposition of the total mediation in percentages (%) by each related mechanism variable in column (1) and the cumulative percentage (%) mediation in column (2). We present the contribution of each self-belief variable in the upper panel of the table and the contribution of each parental-belief variable in the lower panel of the table. We use specification (7) to derive those percentages.

Table 11: Nonlinear Rank Estimates for Each Mechanism Variable

	Self-Belief		Parents' Belief			
	(1) Self-perception in Achievement Rank	(2) Core Subjects Learning Confidence	(3) Parents' Perception of Child's Achievement Rank	(4) Parents' Requirements for Child's Study	(5) **1**(High Expectations for Childs' Educational Level)	(6) **1**(High Expectations for Childs' Career Prospects)
Rank Decile 1	-0.100***	-0.547**	-0.067**	-0.003	-0.086	-0.125
	(0.037)	(0.221)	(0.029)	(0.043)	(0.070)	(0.090)
Rank Decile 2	-0.053**	-0.335*	-0.036	-0.011	-0.067	-0.152**
	(0.026)	(0.183)	(0.022)	(0.035)	(0.051)	(0.067)
Rank Decile 3	-0.026	-0.216	-0.020	-0.025	-0.052	-0.093
	(0.019)	(0.133)	(0.017)	(0.024)	(0.043)	(0.058)
Rank Decile 4	-0.010	-0.242**	0.001	0.001	-0.011	-0.101**
	(0.014)	(0.100)	(0.013)	(0.018)	(0.032)	(0.047)
Rank Decile 6	0.015	0.167*	0.024*	0.026*	-0.007	-0.064
	(0.015)	(0.100)	(0.014)	(0.014)	(0.039)	(0.045)
Rank Decile 7	0.025*	0.038	0.014	0.031	0.036	0.000
	(0.015)	(0.123)	(0.016)	(0.021)	(0.043)	(0.045)
Rank Decile 8	0.052***	0.115	0.032*	0.068**	0.065	-0.028
	(0.019)	(0.157)	(0.019)	(0.028)	(0.057)	(0.053)
Rank Decile 9	0.055**	0.301	0.042*	0.062*	0.095	0.003
	(0.023)	(0.211)	(0.023)	(0.036)	(0.061)	(0.064)
Rank Decile 10	0.063**	0.247	0.043	0.054	0.089	-0.078
	(0.032)	(0.281)	(0.030)	(0.050)	(0.074)	(0.078)
N	3,580	3,544	3,577	3,494	3,505	3,523
Quartic Poly. in 7^{th} Grade Test Scores by School	✓	✓	✓	✓	✓	✓
Student Characteristics	✓	✓	✓	✓	✓	✓
Family Characteristics	✓	✓	✓	✓	✓	✓
Classroom FE	✓	✓	✓	✓	✓	✓

Notes: We split the achievement rank variable into 10 deciles and include them in the model as a set of indicators, with the 5^{th} decile (approximately median ranks) being omitted as the reference group. In the main specification (2), we replace the treatment variable ($rank^0_{i,s,c}$) with a set of decile indicators and obtain estimates for each rank decile. Each column presents the estimates for each rank decile for each mechanism variable. All specifications control for student characteristics, family characteristics, and the 4^{th}-order polynomial functional forms of students' 7^{th} grade test score interacted by school indicators. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

Appendix

Table A.1: Construction of Mechanism Variables from Survey Questions

Variable	Waves Available	Questionnaire Question	Construction
Self-Belief			
Self-perception in Achievement Rank	Wave 1 (2013 Grade 7)	"How does your academic record rank in your class at present?"	We construct the corresponding percentile rank based on a student's perception of rank, assigning the following values: 0 if a student chooses "1. Near the bottom"; 0.25 if "2. Below the average"; 0.5 if "3. About the average"; 0.75 if "4. Above the average"; and 1 if "5. Around the top".
Core Subjects Learning Confidence	Wave 1 (2013 Grade 7)	(1) At present, are the following courses (Mathematics/Chinese/English) difficult for you? (2) Mathematics/Chinese/English helps a lot with my future development.	Each question is subject-specific, with answers to question (1) ranging from "1. Very difficult" to "4. Not difficult at all," and answers to question (2) ranging from "1. Strongly disagree" to "4. Strongly agree". For question (1), we construct a binary variable 1 if the student chooses "4. Not difficult at all" to form the first measure of students' learning confidence for each subject. For question (2), we construct a binary variable 1 if the student chooses "4. Strongly agree" to form the second measure of students' learning confidence. We then aggregate them into student-level measure of subject learning confidence by performing PCA on the six binary variables and using the second principal component scores, which have relatively high loading factors on the first three binary variables from question (1).
Parental-Belief			
Parents' Perception of Child's Achievement Rank	Wave 1 (2013 Grade 7)	"How does this child's academic record rank in his/her class at present?"	We construct the corresponding percentile rank based on parents' perception about rank assigning the following values: as 0 if a parent chooses "1. Near the bottom"; 0.25 if "2. Below the average"; 0.50 if "3. About the average"; 0.75 if "4. Above the average"; and 1.00 if "5. Around the top."
Parental Requirements for Children's Study	Wave 2 (2014 Grade 8)	"What is your requirement on this child's academic record?"	We construct the measure of study requirements based on parents' response, assigning the following values: 0.95 if parents choose "1. Being one of the top five of his/her class"; 0.75 if "2. Above the average"; 0.5 if "3. About the average"; and 0 if "4. No special requirement."
1(High Expectations for Child's Educational Level)	Wave 2 (2014 Grade 8)	"What is the highest level of education do you expect this child to receive?"	We construct a binary variable based on parents' response and assign the value of 1 if parents expect their child to "Get a Master degree" or "Get a Doctor degree" and 0 otherwise.
1(High Expectations for Child's Career Prospects)	Wave 2 (2014 Grade 8)	"What kind of job do you most expect this child to do in the future?"	We construct a binary variable based on parents' response and we assign the value of 1 if parents expect their child to work in white-collar occupations such as "1.Government official, staff of public institutions, civil servant," "2.Manager or administrator of enterprise/corporations," "3.Scientist/engineer/programmer/pilot/spaceman," and "4.Teacher/doctor/lawyer/accountant/translator;" and 0 otherwise.

Teachers' Investment			
(1) Subject Teachers' Attention; (2) Subject Teachers' Praise; (3) Subject Teachers' Question	Wave 2 (2014 Grade 8)	(1) My mathematics/Chinese/English teacher always pays attention to me; (2) My mathematics/Chinese/English teacher always praise me; (3) My mathematics/Chinese/English teacher always ask me to answer questions in class	Each question is subject-specific, with answer ranging from 1 (strongly disagree) to 4 (strongly agree). We code students' response to each subject-specific question as binary variable equals to 1 if the student chooses 4 (strongly agree), separately. We then construct an aggregate student-level measure of teachers' attention, teachers' praise, and teachers' questioning by performing PCA within each question across subjects and using the first principal component scores.
1(Head Teachers' Praise)	Wave 2 (2014 Grade 8)	"My homeroom teacher always praises me"	The response ranges from 1 (strongly disagree) to 4 (strongly agree). We construct a binary indicator that equals one if a student chooses 4 (strongly agree), and 0 otherwise.

Notes: For the original survey questions, see Appendix D.

Table A.2: Variation in rank conditional and unconditional on test score and fixed effects

	Rank Unconditional Test Score	Rank Conditional on Test Score
	(1)	(2)
Std. Dev.	0.285	0.151
Std. Dev. Net of School FE	0.284	0.115
Std. Dev. Net of Classroom FE	0.284	0.101

Notes: Column (1) shows the standard deviation of the 7^{th} grade achievement rank unconditional on school-specific test scores (row 1), net of school FE (row 2), and net of classroom FE (row 3). Column (2) shows the standard deviation of the 7^{th} grade achievement unconditional on school-specific test scores (row 1), net of school FE (row 2), and net of classroom FE (row 3).

Table A.3: Random Assignment of Teachers to Classrooms

Class-Level Mean Characteristics	1(Female Head Teacher) (1)	1(Female Chinese Teacher) (2)	1(Female Math Teacher) (3)	1(Female English Teacher) (4)	1 (Senior Head Teacher) (5)	1 (Senior Chinese Teacher) (6)	1 (Senior Math Teacher) (7)	1 (Senior English Teacher) (8)
Student Characteristics								
Age	-0.614	0.028	-0.026	0.269	0.400	0.403	0.074	0.560
	(0.830)	(0.956)	(2.446)	(0.796)	(0.699)	(1.025)	(1.459)	(0.585)
Female (1=Yes)	-0.321	-0.706	-1.642	0.703	-0.811	0.760	0.538	0.354
	(1.500)	(1.847)	(3.995)	(0.718)	(1.192)	(1.853)	(3.274)	(0.990)
Minority (1=Yes)	0.782	-1.488	-1.613	-0.244	-0.832	1.549	-1.409	0.679
	(2.322)	(1.592)	(5.640)	(1.902)	(1.847)	(3.091)	(3.662)	(2.651)
Only Child in Family (1=Yes)	-0.040	-0.052	1.386	-0.475	-0.318	-0.655	-0.719	0.211
	(0.788)	(0.564)	(1.644)	(0.630)	(0.622)	(2.094)	(1.558)	(0.421)
Attend Kindergarten (1=Yes)	-0.774	-0.287	2.150	-0.392	-0.812	0.326	-2.473	0.550
	(1.474)	(1.670)	(4.394)	(0.587)	(0.866)	(0.875)	(2.260)	(0.971)
Skip Grade in Primary School (1=Yes)	-6.481	-5.511	-0.732	-2.625	-1.061	1.984	-1.797	0.000
	(3.870)	(4.711)	(5.034)	(4.018)	(1.849)	(5.340)	(4.296)	(0.000)
Repeat Grade in Primary School (1=Yes)	-0.931	0.642	3.110	1.308	0.476	0.152	-3.681	-0.197
	(1.551)	(1.062)	(3.867)	(1.768)	(2.232)	(1.100)	(4.275)	(0.356)
Family Characteristics								
Rural Residence (1=Yes)	-0.401	0.506	0.451	0.609	-0.300	-0.393	-0.656	-0.212
	(0.747)	(0.653)	(1.635)	(0.963)	(0.711)	(1.547)	(1.002)	(0.383)
Local Residence (1=Yes)	0.257	0.245	-0.685	-0.014	-0.844	-0.387	1.064	0.164
	(0.384)	(0.577)	(1.835)	(0.260)	(0.306)***	(0.681)	(1.630)	(0.301)
High Income (1=Yes)	0.711	-0.193	1.065	0.839	2.079	3.885	0.030	-0.979
	(1.495)	(3.053)	(2.342)	(1.986)	(1.124)*	(2.321)	(3.077)	(1.607)
Father's Years of Schooling	0.198	0.072	-0.054	0.008	-0.017	-0.079	0.172	-0.029
	(0.134)	(0.133)	(0.185)	(0.060)	(0.094)	(0.203)	(0.199)	(0.107)
Mother's Years of Schooling	0.050	-0.010	0.001	0.049	-0.024	-0.040	0.161	0.015
	(0.110)	(0.088)	(0.215)	(0.136)	(0.101)	(0.261)	(0.185)	(0.197)
N	92	72	66	68	92	71	66	68
School FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean of Dependent Variable:	0.698	0.778	0.682	0.912	0.163	0.211	0.288	0.147

Notes: Each cell presents the estimated coefficient and standard error (in parentheses) from separate regressions, in which the dependent variable is the indicator for head/subject teacher gender (1=Female, in columns 1-4) or the indicator of the seniority of head/subject teacher (1=Senior, in columns 5-8), and the independent variable is the class-level mean of student characteristics in the corresponding row. N is the number of classrooms, which is the unit of observation in the regression. All regressions include school fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at school level.

Table A.4: Estimated Rank Effects using Alternative Ties-Breaking Methods

	(1) Test Score (std) Grade 8	(2) Test Score (std) Grade 8	(3) Test Score (std) Grade 8	(4) Test Score (std) Grade 8
Achievement Rank (Grade 7): High Rank	0.557***			
	(0.186)			
Achievement Rank (Grade 7): Mean Rank		0.592***		
		(0.185)		
Achievement Rank (Grade 7): Low Rank			0.602***	
			(0.183)	
Achievement Rank (Grade 7): Random Rank				0.528***
				(0.180)
N	3,592	3,592	3,592	3,592
Adjusted R^2	0.753	0.753	0.754	0.753
Quartic in 7^{th} Grade Test Scores by School	✓	✓	✓	✓
Student Characteristics	✓	✓	✓	✓
Family Characteristics	✓	✓	✓	✓
Classroom FE	✓	✓	✓	✓

Notes: The table presents estimated rank effects in early grade 7 on students' standardized test scores in the 8^{th} grade while we use different methods to break the ties of students' achievement rank in semester 1 in grade 7. The achievement rank is constructed in four different ways only for students who have the exact same performance in grade 7. Column 1 presents the baseline rank estimate and uses the highest rank in case of ties. In particular, all students tied with the exact same score in grade 7 in their classroom are assigned the highest rank. Column 2 presents the rank estimate when all students tied with the exact same score in early grade 7 in their classroom are assigned the average rank. Column 3 shows the rank estimate when all students tied with the exact same score in early grade 7 in their classroom are assigned the lowest rank. Column 4 shows the rank estimate when all students tied with the exact same score in early grade 7 in their classroom are assigned a random rank. All regressions control for classroom fixed effects, 4^{th}-order polynomial of a student's test score in 7^{th} grade, student characteristics, and family characteristics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

Table A.5: Summary Statistics for Mechanism Variables

Mechanism Variables	Mean (1)	SD (2)	Min (3)	Max (4)	N (5)
Panel A *Channel 1: Self-Belief*					
Self-perception of Achievement Rank	0.550	0.276	0	1	3580
Variables for Constructing Core Subject Learning Confidence PCA scores:					
1(Chinese Subject is Not Difficult At All)	0.175	0.380	0	1	3566
1(Mathematics Subject is Not Difficult At All)	0.154	0.361	0	1	3578
1(English Subject is Not Difficult At All)	0.195	0.397	0	1	3572
1(Chinese Subject Helps a Lot with My Future Development)	0.610	0.488	0	1	3573
1(Mathematics Subject Helps a Lot with My Future Development)	0.545	0.498	0	1	3576
1(English Subject Helps a Lot with My Future Development)	0.597	0.491	0	1	3571
Panel B *Channel Group 2: Parents' Belief*					
Parents' Perception of Child's Achievement Rank	0.533	0.264	0	1	3577
Parents' Requirements for Child's Study	0.733	0.230	0	.95	3494
1(High Expectations for Child's Educational Level)	0.285	0.451	0	1	3505
1(High Expectations for Child's Career Prospect)	0.552	0.497	0	1	3523
Panel C *Channel Group 3: Teachers' Investment*					
Variables for Constructing Subject Teachers' Attention PCA scores:					
1(Chinese Teacher Often Pays Attention to Me)	0.210	0.407	0	1	3538
1(Math Teacher Often Pays Attention to Me)	0.198	0.399	0	1	3539
1(English Teacher Often Pays Attention to Me)	0.231	0.422	0	1	3540
Variables for Constructing Subject Teachers' Praise PCA scores:					
1(Chinese Teacher Often Praises Me)	0.154	0.361	0	1	3536
1(Math Teacher Often Praises Me)	0.146	0.354	0	1	3539
1(English Teacher Often Praises Me)	0.153	0.360	0	1	3531
Variables for Constructing Subject Teachers' Question PCA scores:					
1(Chinese Teacher Often Asks Question of Me)	0.181	0.385	0	1	3533
1(Math Teacher Often Asks Question of Me)	0.165	0.371	0	1	3530
1(English Teacher Often Asks Question of Me)	0.195	0.396	0	1	3526
1(Head Teachers' Praise)	0.108	0.311	0	1	3533

Notes: This table presents the summary statistics for each mechanism variable used in the main analysis. Panel C shows summary statistics for the raw variables that we use to construct the student-level subject teachers' attention, praise, and question PCA scores.

Table A.6: Randomness of Skipping Survey Responses

Dependent Variable	Coefficient (1)	Standard Error (2)	N (3)
1(Missing Self-perception of Achievement Rank)	-0.025	0.016	3592
1(Missing Core Subjects Learning Confidence)	-0.043	0.046	3592
1(Missing Parents' Perception of Child's Achievement Rank)	0.006	0.026	3592
1(Missing Parental Requirements for Children's Study)	0.037	0.063	3592
1(Missing High Expectations for Child's Educational Level)	-0.009	0.065	3592
1(Missing High Expectations for Child's Career Prospects)	0.015	0.052	3592

Notes: The table reports estimated achievement rank effects on the probability of a student or a parent skipping to respond to a survey question related to the mechanism behind rank effects. To derive this we use specification (2), while the outcome variable is now a binary indicator that equals 1 if the survey response is missing. All regressions control for student characteristics, family characteristics, and classroom fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Robust standard errors reported in parentheses are clustered at classroom level.

A Simulation of Confounding Factors

Our main specification (2) examines the impact of achievement rank effects on subsequent scholastic outcomes, conditional on the baseline achievement. One might be concerned that the estimated rank effects could be biased if there are unobserved factors that affect subsequent test scores, and meanwhile perturb achievement rank through its impact on the baseline achievement in a time-varying manner.[44] The hypothesis is that the bias is eliminated once we control for the baseline test score, since including it in the model is equivalent to implicitly control for those unobserved factors. To test this hypothesis, we run a simulation of the data generating process (DGP) of student baseline performance in grade 7 and subsequent performance in grade 8, and introduce an individual-level unobserved factor that determines test scores in both periods. Then, using the simulated data, we estimate rank effects from specifications with and without controls for the baseline test score. Following the spirit of our main identification strategy, we assume the effect of the baseline achievement on subsequent performance is school-specific but linear (without loss of generality). We examine whether the bias in rank effects would be absent if we only control for school-specific baseline test scores without explicitly accounting for the confounding factor. To do so, we first simulate a sample that contains 2,000 students attending 25 schools, with 2 classrooms in each school, and generate a DGP of students' subsequent (grade 8) achievement, $y^1_{i,s,c}$, which depends on the following factors:

- An individual i's (time-invariant) innate ability, α_i, drawn from a standard normal distribution $\mathcal{N}(0, 1)$.

- School and class space-and-time-specific factors, denoted as μ^t_s and μ^t_s (t={0,1}; where 0 represents the current period (grade 7) and 1 the subsequent period (grade 8), respectively. Both are also drawn from $\mathcal{N}(0, 1)$.

- A time-specific confounding factor (i.e., may include unobserved motivation, personal traits, or parental input), $\rho^t_{i,s,c}$, which is defined as strongly correlated with students' true ability α_i and a noise $\upsilon_{i,s,c}$ as follows:

$$\begin{aligned}
&\text{Confounding factor in period 0:}\quad \rho^0_{i,s,c} = \lambda^0\alpha_i + \delta^0\upsilon^0_{i,s,c};\\
&\text{Confounding factor in period 1:}\quad \rho^1_{i,s,c} = \lambda^1\rho^0_{i,s,c} + \delta^1\upsilon^1_{i,s,c};\\
&\text{where:}\quad \lambda^0 = \lambda^1 = 0.9,\ \delta^t = \sqrt{1-(\lambda^t)},\ \text{and } \upsilon^t_{i,s,c} \sim \mathcal{N}(0,1)
\end{aligned} \tag{A.8}$$

To structure the confounding factors in this way we assume that (1) the confounding factors in both periods are drawn from a mixture normal distribution with mean of 0 and variance

[44] If the unobserved characteristics have the same effect on both baseline and subsequent test scores, then controlling for baseline test scores can already partial out the effects of unobservables.

of 1; (2) the confounding factor at $t = 0$, $\rho^0_{i,s,c}$, is highly correlated with ability α_i, with $cov(\alpha_i, \rho^0_{i,s,c}) = \lambda^0$, which is reasonable since a high-ability student would have high motivation to perform better on examinations; and (3) the confounding factor at $t = 1$, $\rho^1_{i,s,c}$, is highly correlated with that at $t = 0$, $\rho^0_{i,s,c}$, with $cov(\rho^1_{isc}, \rho^0_{i,s,c}) = \lambda^1$, which can be interpreted as the high persistence of motivation across periods.

- students' baseline test score $y^0_{i,s,c}$ (in grade 7) and ordinal rank based on the baseline test score $\gamma^0_{i,s,c}$ (see below).

We generate individual i's test score in period 0 and period 1 as a function of innate ability α_i, school factors (i.e., μ^0_s for grade 7 and μ^1_s for grade 8), class factors (i.e., $\tau^0_{s,c}$ for grade 7 and $\tau^1_{s,c}$ for grade 8), confounding factors (i.e., $\rho^0_{i,s,c}$ for grade 7 and $\rho^1_{i,s,c}$ for grade 8), and ordinal rank, $\gamma^0_{i,s,c}$. We assume there is a classical measurement error $\epsilon^t_{i,s,c} \sim \mathcal{N}(0, 1)$ in the test scores in both periods.

Without loss of generality, we set the parameter on innate ability α_i as 0.50 and the parameter on ordinal rank $\alpha^0_{i,s,c}$ as 0.1. To have time-varying and sizeable effects of confounding factors on test scores, we set the parameters on the confounding factor at period $t = 0$ ($\rho^0_{i,s,c}$) as 0.20 and at period $t = 1$ ($\rho^1_{i,s,c}$) as 0.30, and simulate the following DGPs of student performance:

- DGP of Test Scores in grade 7 ($t = 0$):

$$y^0_{i,s,c} = 0.5\alpha_i + \mu^0_s + \tau^0_{s,c} + 0.2\rho^0_{i,s,c} + \epsilon^0_{i,s,c} \tag{A.9}$$

- DGP of Test Scores in grade 8 with rank effects ($t = 1$):

$$y^1_{i,s,c} = 0.5\alpha_i + 0.1\gamma^0_{i,s,c} + \mu^1_s + \tau^1_{s,c} + 0.3\rho^1_{i,s,c} + \epsilon^1_{i,s,c} \tag{A.10}$$

We simulate the above set of DGPs of test scores 1,000 times. Each time, we estimate rank parameter δ_1 from the following specification which follows the same spirit of our main specification (2), with and without controlling ofor school-specific baseline test scores (i.e., the term in parentheses):

$$y^1_{i,s,c} = \delta_0 + \delta_1 rank^0_{i,s,c} + \left(\sum^{S}_{s'} \theta_{s'} y^0_{i,s',c}[\mathbf{1}(s' = s)] \right) + \eta_c + \epsilon^1_{i,s,c} \tag{A.11}$$

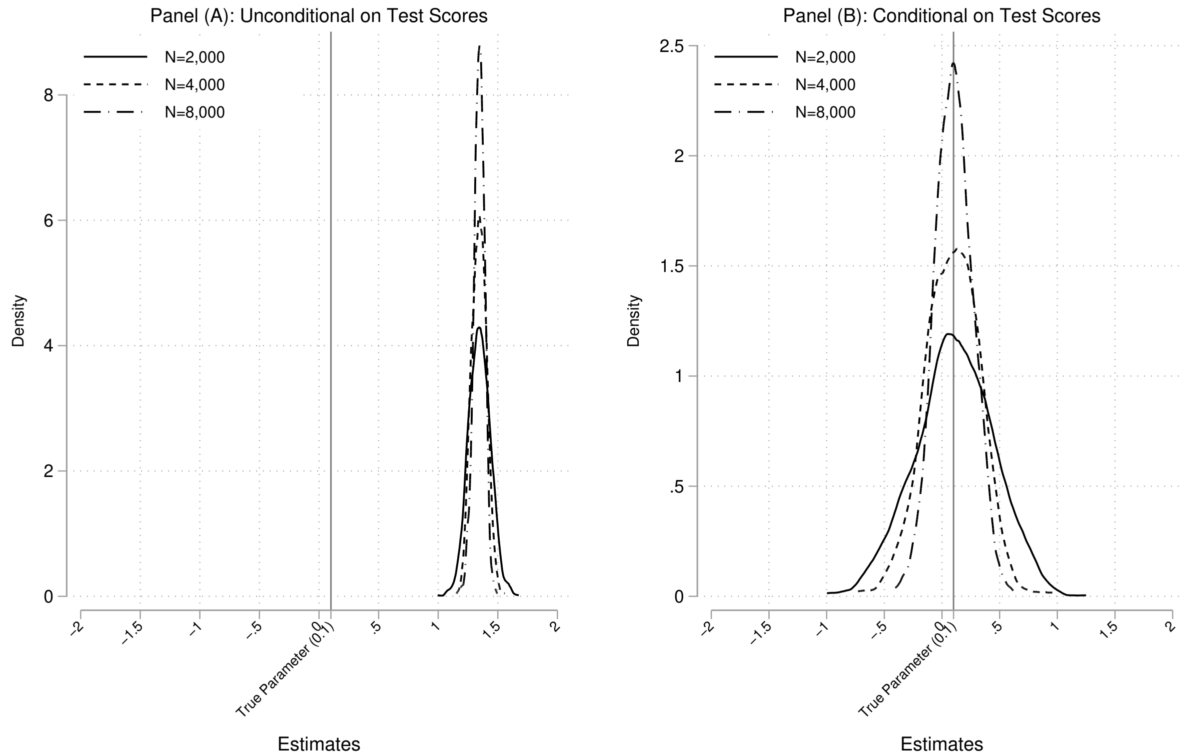
Figure B.1 presents the distributions of rank estimates from specifications unconditional and conditional on school-specific baseline test scores (i.e., shown as Panel (A) and Panel (B), respectively), along with the true rank parameter in the DGP (shown as the vertical line at 0.1 of the x-axis). Since the true rank parameter in the DGP is 0.1, we expect that the average estimated rank effect from the simulated data is also close to 0.1. We first estimate specification (A.11) without controlling for the baseline test scores (i.e., specification (A.11) without the term in parentheses).

Panel (A) shows a significant upward bias in the rank effects, with the distribution of rank effects (solid curve) centered far to the right from the true parameter (vertical line). Such upward bias may be because our rank estimates capture the individual's true ability α_i and any unobserved factors (i.e., the confounding factor $\rho^0_{i,s,c}$ at period 0) that are simultaneously correlated with rank and outcomes. We then estimate specification (A.11) controlling for the baseline test scores (i.e., specification (A.11) including the term in parentheses). Panel (B) shows that the distribution of rank effects centers around the true parameter and there is no remaining bias, even if specification (A.11) does not explicitly account for the confounding factors in any periods.

After verifying the unbiasedness of the rank estimates (that is, $E[\hat{\delta_1}|\text{control}] = \delta_1$), we further check the consistency of these rank estimates (that is, $plim_{N\rightarrow\infty}\hat{\delta_1} = \delta_1$). We enlarge the simulated sample size to (1) 4,000 students allocated 50 schools and 100 classrooms and (2) 8,000 students in 100 schools and 200 classrooms, replicate the aforementioned simulation and estimation, and plot the corresponding distribution of rank effect estimates. We incorporate these new estimates in Panels A and B in Figure B.1. We observe convergence of rank effect estimates in both panels. In Panel A, we see that the distributions of those estimates (dashed and dotted curves) would converge to a wrong parameter if the baseline achievement was omitted in specification (A.11). However, in Panel B, we notice that the distribution of estimates (dashed and dotted curves) would converge to the true parameter when we control for the baseline achievement in specification (A.11), even if potential confounders were neglected.

These simulation results suggest that any confounding factors that might influence outcomes and rank through baseline test scores should not bias the rank effects as long as we control for baseline test scores in the regression. Rank effect estimates can also be consistently estimated. That may be because this type of confounding factor does not introduce measurement error in test scores and therefore does not transit measurement error into ordinal rank to then bias the estimated rank effect parameter.

Figure B.1: Simulated DGP with Time-Varying Confounding Factor in Test Scores



Notes: Panel (A) plots the distribution of estimates of rank effects generated by 1,000 simulations of equations (A.9) and (A.10) and estimations of equation (A.11) *without controlling for school-specific baseline test score*, based on different samples: 2,000 individuals in 25 schools and 50 classrooms (N=2,000); 4,000 individuals in 50 schools and 100 classrooms (N=4,000); and 8,000 individuals in 100 schools and 200 classrooms (N=8,000). Panel (B) plots the simulated distributions of rank effect estimates generated by equation (A.11) *controlling for school-specific baseline test score*, based on the same set of sample sizes. The vertical line represents the true parameter of rank in the DGP.

B Simulation of Measurement Error in Test Scores

B.1 Test Score-Independent Measurement Error

We first consider an individual-level measurement error that is *independent* of student baseline and subsequent test scores. Specifically, we define the measurement error, ϵ_s^t, to be time-(t)-and school (s)-specific, which is drawn from a normal distribution with mean zero and standard deviation σ_s^t that is proportional to the school-level standard deviation of test scores at both periods, denoted as δ_s^t ($t = \{0,1\}$). That is, an individual's test scores $\bar{y}_s^t$ (here, we suppress the individual and classroom notations i and c for simplicity) augmented by measurement error ϵ_s^t in both periods are constructed as:

$$\bar{y}_s^t = y_s^t + \epsilon_s^t; \quad \epsilon_s^t \sim \mathcal{N}(0, (\sigma_s^t)^2); \quad \sigma_s^t \propto \delta_s^t; \quad t = \{0,1\} \tag{B.1}$$

We examine how measurement error would bias our estimates and divide the analysis into two parts: (1) introduce individual-level measurement error ϵ_s^t only into the baseline achievement y_s^0 and (2) introduce individual-level measurement error ϵ_s^t into both baseline achievement y_s^0 and subsequent achievement y_s^1.

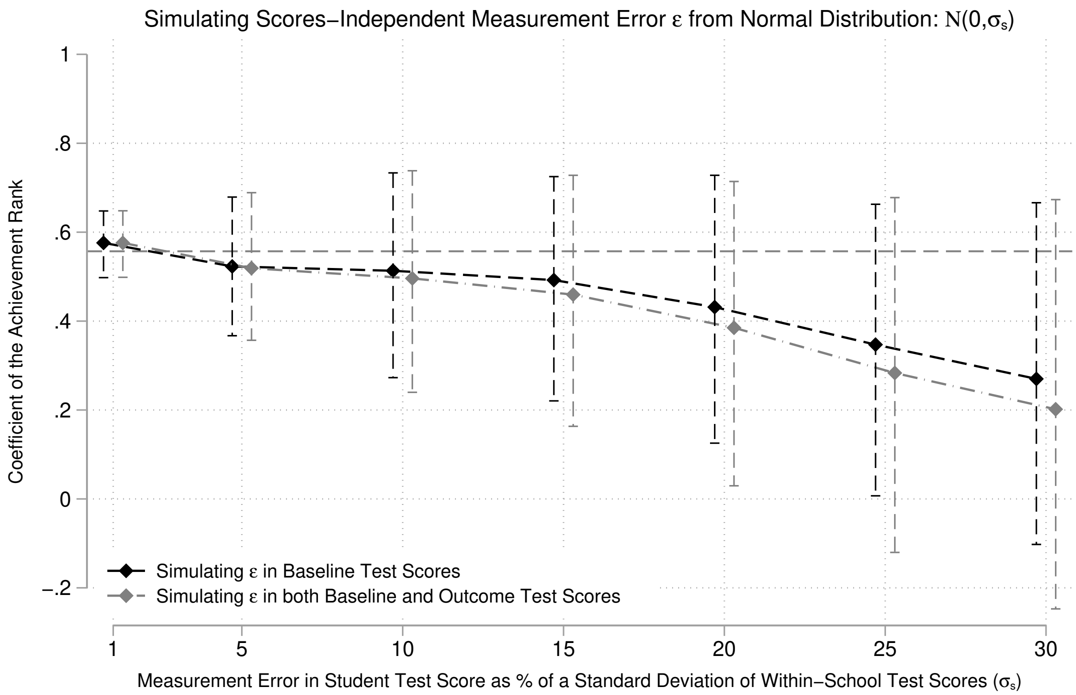
For the first part of the analysis, we only simulate measurement error and feed it into the baseline achievement to form $\bar{y}_t^0$. We then recalculate the achievement rank based on $\bar{y}_t^0$ and re-estimate the rank effects using specification (2). To see how the direction and magnitude of the bias of rank estimate evolves, we increase the standard deviation of the distribution of measurement error (σ_s^t) from 1% of the standard deviation of the test score within a school (i.e., δ_s^t, which is equivalent to 0.44 points in 7$^{\text{th}}$ grade and 0.53 points in 8$^{\text{th}}$ grade on average) up to 30% (equivalent to 13.29 points in 7$^{\text{th}}$ grade and 16.06 points in 8$^{\text{th}}$ grade).[45] To obtain an empirical confidence interval, we simulate 1,000 times for each level of measurement error distribution and perform the estimation. For the second part of the analysis, we use the same aforementioned procedure and simulate the measurement error in both the baseline and subsequent achievement.

Figure B.1 shows the means and the 95% empirical confidence intervals of the simulated rank effect estimates at each level of the standard deviation of measurement error, with the horizontal line at 0.577 representing baseline rank effect estimates. This indicates that when there is only measurement error in the baseline test score (in black), rank estimates exhibit a downward bias as the measurement error in baseline test scores increases. Additive measurement error has little influence on rank effect estimates when it is small (i.e., 1% of school-level standard deviation). At levels of measurement error larger than 5% of the school-level standard deviation (i.e., equivalent to 2.15 points), estimates attenuate quickly. At levels of measurement error larger than 15% of the school-level standard deviation, rank estimates become statistically insignificant. On the other

[45] The school-level standard deviation in test scores on average is 44.30 in 7$^{\text{th}}$ grade and 53.55 in 8$^{\text{th}}$ grade.

hand, when the measurement error exists in both baseline and subsequent test scores (gray), we find a more pronounced attenuation pattern at each level of measurement error. This pattern is in line with the attenuation pattern in Murphy and Weinhardt (2020).

Figure B.1: Estimation of Rank Effects From a Specification with Simulated Score-Independent Measurement Error in Test Scores



Notes: This figure plots the mean rank estimates from 1,000 simulations of specification (2) with additionally increasing measurement error ϵ drawn from a normal distribution defined as equation (B.1) (from 1% to 30% of the school-specific standard deviation of test scores). The black coefficient plot traces the changes in rank effect estimates due to measurement error at each level of standard deviation only in baseline test scores. The gray coefficient plot traces the changes in rank effect estimates from measurement error in both baseline and subsequent test scores. The horizontal line shows baseline rank effect estimate at (0.557). Bars represent 95% empirical confidence intervals, with the upper bound and the lower bound represented by the 97.5^{th} and 2.5^{th} percentiles from the sampling distribution of simulated rank estimates at each level of measurement error.

B.2 Test Score-Dependent Measurement Error

In this section, we perform a simulation of test score measurement error that is *dependent* on the location of one's baseline and subsequent test score in test score distributions within schools. Specifically, we draw a measurement error ϵ_s^t from a normal distribution with mean 0 and variance that is proportional to the *distance* between an individual's test score and the mean test score at school level. By doing so, we would produce a potentially high measurement error for the student if their test score significantly deviates from the school average. Conceptually, we introduce this type of measurement error in test scores in the following structure (notation for individual i and classroom c are suppressed in $\bar{y}_s^t$ and ϵ_s^t for simplicity):

$$\begin{aligned}\bar{y}_s^t &= y_s^t + \epsilon_s^t \\ &= y_s^t + dis(y_s^t, \mu_s^t) \times \upsilon_s^t; \quad \upsilon_s^t \sim \mathcal{N}(0, (\sigma_s^t)^2); \quad \sigma_s^t \propto \delta_s^t; \quad t = \{0, 1\}\end{aligned} \tag{B.2}$$

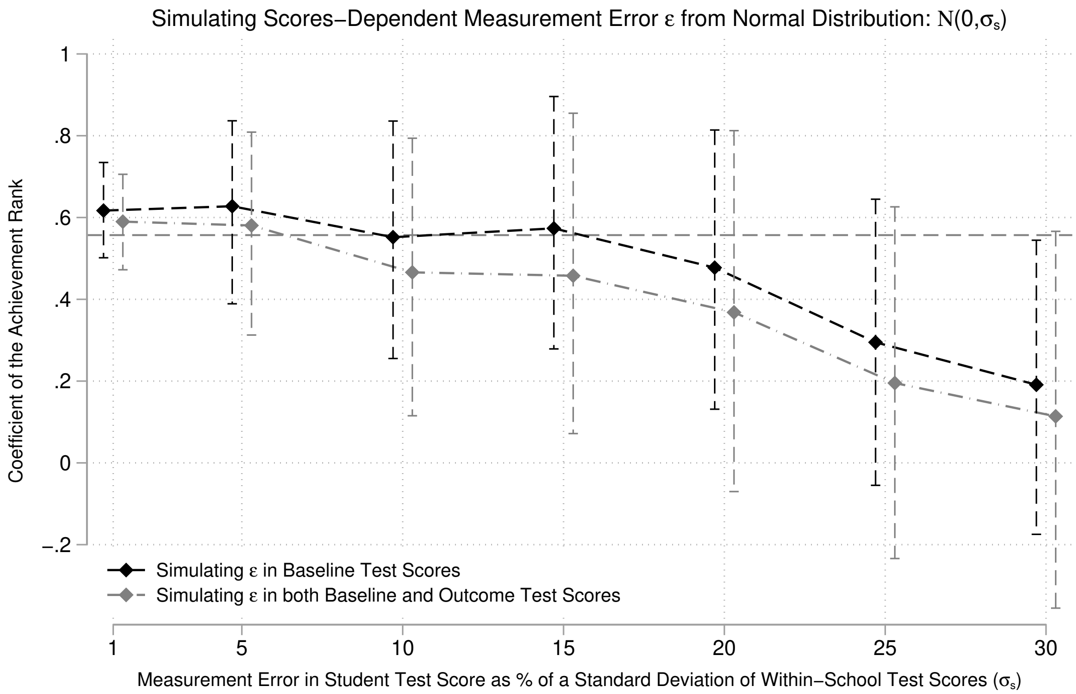
where $\epsilon_s^t = dis(y_s^t, \mu_s^t) \times \upsilon_s^t$. The distance function $dis(y_s^t, \mu_s^t)$ denotes the distance between own score y_s^t and mean score μ_s^t at school s. The randomness of ϵ_s^t comes from the υ_s^t, which is drawn from a normal distribution with mean 0 the standard deviation σ_s^t that is proportional to the standard deviation of test scores within school s, denoted as δ_s^t. To normalize the distance, we define the distance function using the percentalized score within schools as the following:

$$dis(y_s^t, \mu_s^t) = \left| \frac{p(y_s^t) - p(\mu_s^t)}{p(y_s^{t,\max}) - p(y_s^{t,\min})} \right| \times 2 = \left| \frac{p(y_s^t) - 50}{100} \right| \times 2 \tag{B.3}$$

where $p(.)$ denotes the percentalized function of test score y_s^t. The percentalized school-level mean test score $p(\mu_s^t)$ is therefore 50, which is same across schools, and $p(y_s^{t,\max}) - p(y_s^{t,\min})$ is 100. By constructing distance in this way, we effectively transform the original test score distribution into a uniform distribution $\mathcal{U}(-1, 1)$ centered at the school average. If an individual test score y_s^t is close to the school-level mean, the distance is close to 0, and the test score would contain little measurement error; if the score y_s^t is far from the mean (i.e., at the tails of the original distribution), the distance is close to 1, and the test score would contain a high amount of measurement error. By doing so, we allow test scores to become a less precise measure for true ability when it is at the extreme value.

Practically, we scale up this distance function by 5 (i.e., $5 \times dis(y_s^t, \mu_s^t)$) to ensure sufficiently large measurement error in the test score when it is far from the school mean. We tune the parameter σ_s^t by increasing it from 1% of the standard deviation in test scores within the school (δ_s^t) up to 30% and trace the change in rank effects. Following the same approach in Section B.1, we estimate the effect from the simulated rank in two simulation exercises: (1) simulate measurement error only in the baseline test scores and (2) simulate measurement error in both baseline and outcome test scores. Figure B.2 plots the point estimates of rank effects on par with their 95% empirical confidence intervals from 1,000 simulations, with the ever-increasing variance of measurement error. The results show a pattern similar to the case of independent measurement error (Section B.1): The rank effects exhibit an attenuation pattern in general, and the attenuation becomes more pronounced when measurement error exists in both baseline and subsequent test scores (gray coefficient plot).

Figure B.2: Estimation of Rank Effects From a Specification with Simulated Score-Dependent Measurement Error in Test Scores



Notes: This figure plots the mean rank estimates from 1,000 simulations of specification (2) with additionally increasing measurement error ϵ drawn from a normal distribution defined as equation (B.2) (from 1% to 30% of the school-specific standard deviation of test scores). The black coefficient plot traces changes in rank effect estimates due to measurement error at each level of standard deviation only in baseline test scores. The gray coefficient plot traces changes in rank effect estimates from measurement error in both baseline and subsequent test scores. The horizontal line shows the baseline rank effect estimate at (0.557). Bars represent 95% empirical confidence intervals, with the upper bound and lower bound represented by the 97.5$^{\text{th}}$ and 2.5$^{\text{th}}$ percentiles from the sampling distribution of simulated rank estimates at each level of measurement error.

C Derivation

In this section, we show the derivation of equation (7) and discuss the assumptions that ensure a consistent estimate for the mediation factors. For simplification, we suppress the notation i, s, c and nest the control variables $\boldsymbol{X}$, $\sum_{s'}^{S} G(y^0_{i,s',c})[\mathbf{1}(s' = s)]$ and classroom fixed effects into a matrix $\boldsymbol{W}$.

To begin with the derivation, we rewrite equation (C.1) as follows:

$$m^q = \alpha^q + \beta^q rank^0 + \boldsymbol{W}\boldsymbol{\Gamma}^q + \epsilon^q; \qquad q \in \{1, ..., Q\} \tag{C.1}$$

where $\boldsymbol{\Gamma}^q$ includes mechanism q-specific coefficients on the term $\sum_{s'}^{S} G(y^0_{i,s',c})[\mathbf{1}(s' = s)]$, coefficients on $\boldsymbol{X}$, and classroom fixed effects η^q. Next, we rewrite equation (6) as follows:

$$y^1 = \alpha' + \beta' rank^0 + \sum_{q=1}^{Q} \lambda^q m^q + \boldsymbol{W}\boldsymbol{\Gamma} + \epsilon^{1'} \tag{C.2}$$

Feeding equation (C.1) into (C.2), we obtain equation (C.3) :

$$y^1 = \underbrace{(\alpha' + \sum_{q=1}^{Q} \lambda^q \alpha^q)}_{\alpha} + \underbrace{(\beta' + \sum_{q=1}^{Q} \lambda^q \beta^q)}_{\beta} rank^0 + \underbrace{\boldsymbol{W}(\boldsymbol{\Gamma} + \sum_{q=1}^{Q} \boldsymbol{\Gamma}^q)}_{\sum_{s'}^{S} G(y^0_{i,s',c})[\mathbf{1}(s'=s)] + X_{i,s,c}\boldsymbol{\gamma} + \eta_c} + \underbrace{(\epsilon^{1'} + \sum_{q=1}^{Q} \lambda^q \epsilon^q)}_{\epsilon^1_{i,s,c}} \tag{C.3}$$

Essentially, equation (C.3) is our main specification (2), whereby we can have equation (C.4):

$$\hat{\beta} = \hat{\beta}' + \sum_{q=1}^{Q} \hat{\lambda}^q \hat{\beta}^q \tag{C.4}$$

$\hat{\beta}$ is the overall rank effect. $\sum_{q=1}^{q} \hat{\lambda}^q \hat{\beta}^q$ is the total indirect rank effect that initiates its causal effect from the ranks to the outcome through the mechanisms. $\hat{\beta}'$ is the direct rank effect that cannot be explained by the observed mechanisms.

We recognize that for equation (C.4) to be true, we need to ensure that $\hat{\beta}^q$, $\hat{\lambda}^q$, and $\hat{\beta}'$ can all be consistently estimated. The consistency of $\hat{\beta}^q$ is unlikely to be violated as we use exactly the same specification (see equation (C.1)) as the main model, in which the RHS variables are all predetermined and conditionally random. However, for the consistency of $\hat{\lambda}^q$ and $\hat{\beta}'$, we need to assume that all observed (or measured) mechanism components m^q are correctly measured and independent of the unobserved mechanisms captured in the $\epsilon^{1'}$ in the equation (C.2). We recognize that this is a relatively strong assumption. Therefore, we only interpret our decomposition results as an approximation of the relative importance of the mediators.

D Survey Questions

The following shows the original questions in students' and parents' questionnaires that are used to construct mechanisms:

1. Student Self-Belief:

(1). Self-perception in Rank:

C12. How does your academic record rank in your class at present?

1. Near the bottom 2. Below the average 3. About the average
4. Above the average 5. Around the top

(2). Core Subjects Learning Confidence:

C11. AT PRESENT, are the following courses difficult for you?

	Very difficult	A bit difficult	Not very difficult	Not difficult at all
Mathematics	1	2	3	4
Chinese	1	2	3	4
English	1	2	3	4

C13. How much do you agree with each of the following statements about the main subjects?

	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
Mathematics helps a lot with my future development.	1	2	3	4
Chinese helps a lot with my future development.	1	2	3	4
English helps a lot with my future development.	1	2	3	4

2. Parents' Belief

(1). Parents' Perception on Child's Rank

C10. How does this child's academic record rank in his/her class at present?

1. Near the bottom 2. Below the average 3. About the average
4. Above the average 5. Around the top

(2). Parents' Requirement on Child's Study

C11. What is your requirement on this child's academic record?

1. Being one of the top five of his/her class 2. Above the average
3. About the average 4. No special requirement

(3.) 1(High Expectation on Child's Educational Level)

A29. What is the highest level of education do you expect this child to receive?

1. Drop out now
2. Graduate from junior high school
3. Go to technical secondary school or technical school
4. Go to vocational high school
5. Go to senior high school
6. Graduate from junior college
7. Get a bachelor degree
8. Get a Master degree
9. Get a Doctor degree

(4). 1(High Expectation on Child's Career Prospect)

A30. What kind of job do parents MOST expect this child to do in the future?

1. Government official, staff of public institutions, civil servant
2. Manager or administrator of enterprises/corporations
3. Scientist/engineer/programmer/pilot/spaceman
4. Teacher/doctor/lawyer/accountant/translator
5. Professional designer (such as costume, gardening, or advertisement designer)
6. Artistic performer (including writer/drawer/host/director/screenwriter)
7. Professional athlete
8. Technical worker (including driver/cook/maintenance staff)
9. Soldier/policeman
10. Medium service staff (including stewardess/nurse/barber/cosmetologist), or ordinary office staff
11. Self-employed (such as opening a store)
12. Other (Please specify: __________)
13. I don't care

2. Teachers' Investment

(1). Subject Teachers' Attention (Sourced from the first 3 questions)

(2). Subject Teachers' Question (Sourced from the middle 3 questions)

(3). Subject Teachers' Praise (Sourced from the last 3 questions)

B5. How much do you agree with each of the following statements about the main subjects?

	Strongly disagree	Somewhat disagree	Somewhat agree	Strongly agree
My mathematics teacher always pays attention to me.	1	2	3	4
My Chinese teacher always pays attention to me.	1	2	3	4
My English teacher always pays attention to me.	1	2	3	4
My mathematics teacher always asks me to answer questions in class.	1	2	3	4
My Chinese teacher always asks me to answer questions in class.	1	2	3	4
My English teacher always asks me to answer questions in class.	1	2	3	4
My mathematics teacher always praises me.	1	2	3	4
My Chinese teacher always praises me.	1	2	3	4
My English teacher always praises me.	1	2	3	4

(4). 1(Head Teachers' Praise)

My homeroom teacher always praises me.	1	2	3	4