The Asymmetric Effects of High Achiever Peers: Experimental Evidence from Ecuador*

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Abstract

We study the impact of exposure to high achievers on cognitive and non-cognitive skills using a unique randomized experiment from Ecuador. In each school, students are randomly assigned to classrooms in every grade from Kindergarten to 6th. We find that exposure to high achievers reduces test scores in math and executive function. Moreover, male students affect only males, and female students affect only females, consistent with homophily. Peer effects are intensified among top-performing students and students in smaller schools. Effects of 1st-grade peers are stronger but fade over time. Finally, we find reductions in self-reported happiness.

Keywords: High Achievers, Peer effects, Elementary School

JEL: I21, J16

Please note that an Online Appendix is included.

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1 Introduction

Peer effects significantly shape behavior, performance, and decision-making across education, the workplace, and social environments.[1] In education, previous studies show that classroom composition influences student outcomes through various channels, including class size (Hoxby, 2000b), peers' academic achievement (Hanushek et al., 2003), gender composition (Hoxby, 2000a), social interactions (Card and Giuliano, 2013), and relative class rank (Murphy and Weinhardt, 2020; Carneiro et al., 2025). Given the long-term consequences of early childhood development, it is critical to understand how peer composition influences educational outcomes in elementary schools, especially in developing countries where resource constraints and institutional incentives differ substantially.

The impact of exposure to high-achieving peers is theoretically ambiguous and empirically mixed. Although some studies find positive effects on achievement (Balestra et al., 2023), aspirations, and long-term outcomes (de Gendre and Salamanca, 2020; Bertoni et al., 2020), others find negative impacts, particularly when exposure lowers students' relative class rank or increases competition (de Roux and Riehl, 2022; Chen and Hu, 2024).[2] However, most of this research focuses on older students in developed countries and emphasizes test scores as the primary outcome. In this paper, we study how high-achieving peers affect both cognitive and non-cognitive skills throughout elementary school, an early and critical period when peer exposure is intense and in which cognitive and non-cognitive skills are strong predictors of long-term outcomes (Moffitt et al., 2011; Heckman et al., 2006, 2013).

We estimate how the proportion of high achievers, identified through teacher rankings of students' performance, affects cognitive (math and executive function) and non-cognitive skills (depression, self-esteem, growth mindset, and grit). We use data from a unique randomized experiment involving the 2012 entering Kindergarten cohort across 202 elementary

[1] See Carrell et al. (2009); Sacerdote (2011); Card and Giuliano (2013); Sacerdote (2014); Feld and Zölitz (2017, 2022) for education settings; Guryan et al. (2009); Cornelissen et al. (2017); Villeval (2020) for workplace settings.

[2] These effects may also vary across student subgroups, such as high-achieving girls (Cools et al., 2022) or students from more advantaged backgrounds (Bertoni et al., 2020).

schools in Ecuador. For this cohort, we observe rich longitudinal data spanning seven consecutive years, including baseline characteristics, test scores, non-cognitive skills, teacher characteristics, and teacher quality indicators.

At the beginning of each grade, from Kindergarten through 6th grade, students were randomly assigned to classrooms within their schools, each of which had at least two classrooms per grade. Compliance with the random assignment was nearly perfect (98.9% on average). Students who remained in the same school thus experienced seven exogenous, orthogonal peer groups. The variation in the proportion of high achievers across classrooms is attributable to this random assignment, enabling us to causally identify the effects of high achievers on both cognitive and non-cognitive skills.[3]

We identify high achievers using information reported by their teachers. At the end of each grade, we asked teachers to identify the five students with the highest learning in their class. A student is classified as a high achiever if at least 50% of the teachers who observed them in previous grades identified them as such, reducing concerns about measurement error or biases in any single teacher. Based on this classification, we construct the leave-one-out proportion of high achievers in each classroom.

In the main specification, we include school-by-grade fixed effects, which allow us to compare children who attended the same school and grade but were randomly assigned to different classrooms, thus exposing them to exogenous variation in the proportion of high achievers. We find that a one standard deviation increase in the leave-one-out proportion of high achievers reduces math test scores by 0.011 SD and executive function, a set of basic self-regulatory skills, by 0.014 SD. Alongside these reductions in cognitive skills, we find no effect on non-cognitive skills in 6th grade and a decrease in self-reported happiness in 1st grade. These results are robust across various specifications, estimation methods, and alternative definitions of high achievers (detailed in section 4.2). Moreover, when separating by gender, we find that male high achievers affect only male students, and female high

[3]Classroom and teacher quality vary but are orthogonal to peer quality, as teachers were also randomly assigned within schools and grades.

achievers affect only female students. This pattern aligns with observed friendship networks in our data, suggesting that peer effects operate primarily within same-gender interactions, as discussed in Section 4.1. These findings highlight the importance of accounting for both peer and gender composition when evaluating the effects of classroom environments on cognitive development.

While we cannot conclusively distinguish between different mechanisms, our findings suggest that the negative effects of exposure to high achievers are concentrated in environments with heightened competition, greater peer interaction, and increased salience of relative class rank. First, the adverse effects are largest for high-performing children, whose math test scores decrease by 0.030 SD and who experience declines in happiness. These results hold after controlling for classroom rank, suggesting that the effects are not driven by mechanical reductions in students' relative rank within the class. Second, the negative effects are more pronounced in classrooms with more high achievers (on average, eight) and in smaller schools, particularly those with many high achievers.

We also analyze how teacher quality mediates peer effects. Using detailed observational data on teacher behaviors, we find that higher-quality teachers, particularly those skilled in classroom organization, can mitigate the detrimental effects. These results highlight the critical role teachers play in lessening the negative impact of high achievers, especially through effective classroom organization and group management. Moreover, the findings underscore the need to understand how peer effects unfold in classrooms with less effective teachers, and the specific channels through which teacher practices mediate peer effects.

A potential concern in estimating peer effects under random classroom assignment is the weak variation in peer composition as classroom size increases (Angrist, 2014). In our setting, identification relies on residual variation in the proportion of high achievers due to finite-sample imbalances in classroom assignments. To assess this variation, we examine whether the number of high achievers assigned to each classroom follows a hypergeometric distribution with school-specific parameters. Only 8.2% of classrooms have a number of high achievers

that lies outside the 95% confidence interval implied by this distribution. Furthermore, the 90th and 10th percentiles of the observed distribution are 7 and 2, compared to expected values of 6.7 and 2.9, respectively. These results suggest that the observed variation in peer composition is consistent with theoretical expectations. Additional diagnostic analyses, described in Section 3.1, further support the validity of our empirical strategy.

This paper contributes to the literature in four ways. First, it adds to the experimental evidence on peer composition in learning environments. While previous studies have studied random peer assignment in middle schools (Busso and Frisancho, 2021), boarding schools (Zárate, 2023) and college settings (Sacerdote, 2001; Carrell et al., 2009, 2013; Sacerdote, 2014; Feld and Zölitz, 2017, 2022), our study focuses on elementary school, where peer exposure is more intense. We leverage a unique experiment with repeated random assignment and nearly perfect compliance to estimate the causal effects of high-achieving peers and their non-linear impacts.

Second, we extend the literature on the effects of high achievers beyond academic achievement (Balestra et al., 2023), admission scores (Busso and Frisancho, 2021), and long-term outcomes (Cools et al., 2022; Mouganie and Wang, 2020; Bertoni et al., 2020), by studying effects on executive function and non-cognitive skills. Our rich data on teacher quality allow us to analyze how peer effects interact with other classroom inputs. We also find that effects are stronger in environments with heightened competition, greater peer interaction, and increased salience of relative class rank.[4] While related to class rank effects studied in Carneiro et al. (2025), our results are not mechanically driven by reductions in students' relative rank alone; instead, both peer composition and rank independently shape student outcomes.

Third, we contribute to the literature on the timing and persistence of the effects of educational inputs (Jacob et al., 2010; Chetty et al., 2014b; Golsteyn et al., 2021; Carneiro et al., 2025). A novel aspect of our study is the ability to estimate how peer composition

[4]See de Roux and Riehl (2022); Chen and Hu (2024) for a review of university settings

effects vary across grades and evolve over time. We show that these effects are largest in early grades, particularly in 1st grade, and decline significantly as children age.

Finally, our findings inform student-grouping policies, especially in developing countries where peer effecs may differ due to larger class sizes, tighter resource constraints, and institutional settings.[5] We provide new evidence from elementary schools in Ecuador, underscoring the importance of accounting for context-specific peer dynamics and institutional settings when designing grouping policies to improve student outcomes (Mouganie and Wang, 2020; Busso and Frisancho, 2021; Chen and Hu, 2024).

The remainder of the paper is organized as follows. Information about Ecuador, the experimental setting, and data can be found in section 2. Section 3 outlines the empirical strategy. Section 4 provides the main results, the dynamics of the effects, and heterogeneity analysis. Conclusions and policy discussion can be found in section 5.

2 Setting and Data

2.1 Education system in Ecuador

Ecuador is a middle-income country and one of the smallest in South America, with a population of 15.7 million and a GDP per capita of approximately $11.300 (in PPP U.S. dollars) in 2013. Schooling is compulsory from ages 5 to 14. The education system is divided into elementary school (Kindergarten through 6th grade), middle school (7th through 9th grades), and high school (10th through 12th grades). The school year follows a dual-calendar system. In the coastal region, it runs from May to February (similar to most countries in the Southern Hemisphere and many in Latin America), while in the highlands and Oriente (eastern) regions, it runs from September to June (similar to most countries in the Northern Hemisphere).[6]

[5] See Sacerdote (2011, 2014) for a review of previous studies.

[6] According to the 2010 census, 53% of the population lived on the coast, 42% lived in the highlands, and 5% in the Oriente region.

Approximately 4.4 million children were enrolled in the education system during the 2012–2013 school year, with 78 percent attending public schools.[7] Ecuador has made significant progress in expanding access to education. In 2013, the primary school net enrollment rate was 95%, with a completion rate of 97%.[8] However, math achievement among young children remains low (Berlinski and Schady, 2015; Näslund-Hadley and Bando, 2015). For instance, in 2013, only 48.4% of primary school children achieved the minimum proficiency level in mathematics, with a slight gender gap—49.8% for males compared to 46.7% for females.[9] Therefore, like many Latin American nations, Ecuador's critical educational challenge is quality, not access.

The system employs more than 208,000 teachers in the public sector, with salaries primarily determined by seniority. Around 53% of teachers in Ecuador hold tenure, while the remaining 47% work on a contract basis. Between 2012 and 2019, the proportion of qualified teachers in primary increased from 80.1% to 89.3%, contributing to improvements in both the quality of the education system and the instruction provided to students.[10]. However, key challenges persist. For example, the pupil-qualified teacher ratio remained stable at around 27.5 during this period.[11]

2.2 Experimental setting

We use a unique experiment conducted in 202 schools in Ecuador, representative of the country's public education system in the coastal region, to study how peer composition

[7]Data obtained from https://educacion.gob.ec/datos-abiertos/ on November 4th, 2024

[8]The net enrolment rate is the fraction of children of school age who are enrolled in school, while the completion rate corresponds to the percentage of children that have finished the last grade of primary.

[9]This corresponds to the percentage of children in primary that exceed the minimum proficiency level (MPL) which is the pre-defined proficiency level of basic knowledge in mathematics measured through learning assessments. All data were obtained from the World Development Indicators (https://datatopics.worldbank.org/world-development-indicators/) on November 4th, 2024

[10]This corresponds to the fraction of teachers with the minimum academic qualifications required for teaching in primary school.

[11]All data were obtained from the World Development Indicators (https://datatopics.worldbank.org/world-development-indicators/

impacts cognitive and non-cognitive skills.[12] Each school had at least two classrooms per grade, with most having exactly two. In the 2012 school year, an incoming cohort of children was randomly assigned to Kindergarten classrooms within each school. These children were then randomly reassigned to classrooms in subsequent grades through 6th grade in 2018. Compliance with the assignment rules was very high, averaging 98.9% (Carneiro et al., 2025). As a result, children who remained in the same school throughout elementary school were exposed to seven exogenous, orthogonal shocks to classroom composition.[13]

The random assignment allows us to address concerns about the purposeful matching of students with teachers and peers, a common issue in non-experimental settings (Chetty et al., 2014a; Rothstein, 2010).[14] To test the success of the random assignment, we apply the method proposed by Jochmans (2023), which checks for correlation between student i's end-of-grade scores in year $t-1$ and the average scores in $t-1$ of the classroom peers assigned to her in year t. As shown in Appendix Table B.1, we cannot reject the null hypothesis that there is no correlation between child i's achievement and that of her classroom peers, confirming that the random assignment was successful. Further details on the classroom assignment rules, randomization tests, and compliance with randomization are provided in Appendix B.

[12]These schools are a random sample of all public schools with at least two Kindergarten classrooms in the Ecuador's coastal region 2012. See Araujo et al. (2016) for more details on the school selection. Morevover, they show that the characteristics of students and teachers in the sample closely resemble those in a nationally representative sample of schools in Ecuador.

[13]It is worth noting that random reassignment may separate students from their friends. However, out-of-class friendship ties are orthogonal to peer composition given the random assignment.

[14]We use the term "random" for simplicity, but strictly speaking, random assignment only occurred from 3rd to 6th grade. In the other grades, the assignment rules were as-good-as-random. Specifically, in Kindergarten, children were ordered by their last and first names and then assigned to teachers in alternating order. In 1st grade, they were ordered by date of birth, from oldest to youngest, and assigned to teachers in alternating order. In 2nd grade, they were divided by gender, ordered by first and last names, and then assigned in alternating order. From 3rd to 6th grades, students were separated by gender and randomly assigned to classrooms.

2.3 Data

2.3.1 Child data

At the beginning of Kindergarten, we collected baseline data on maternal education, household wealth, preschool attendance, and children's vocabulary skills.[15] We administered age-appropriate math tests at the end of each grade from Kindergarten to 6th grade. These tests included material that teachers were expected to have covered explicitly in class (e.g., addition or subtraction), material that may have been covered during the academic year but in a somewhat different format (e.g., simple word problems), and material that was not covered in class but has been shown to predict current and future math achievement (e.g., the Siegler number line task).[16] We aggregated correct math responses for each component separately using Item Response Theory (IRT) and then computed the total math score, with each component receiving equal weight.

Additionally, we collected data on executive function for each grade from Kindergarten to 4th grade. Executive function encompasses a set of self-regulatory skills involving various regions of the brain, particularly the prefrontal cortex. It is generally divided into three domains: working memory and attention, inhibitory control, and cognitive flexibility.[17] These skills are crucial for young children to adapt and learn effectively in school, as they are needed to pay attention, take turns, ask questions, remember steps, and solve math

[15] To measure baseline receptive vocabulary, we use the Test de Vocabulario en Imágenes Peabody (TVIP), the Spanish-speaking version of the widely-used Peabody Picture Vocabulary Test (PPVT) (Dunn et al., 2015). The TVIP was normed on samples of Mexican and Puerto Rican children and has been widely employed to assess verbal ability and development among Latin American children.

[16] The number line task works as follows: children are shown a line with endpoints marked. For example, in 1st grade, the left end of the line is marked with 0, and the right end with a 20. They are then asked to place various numbers on the line (e.g., 2 or 18). The accuracy with which children place the numbers has been shown to predict general math achievement (see Siegler and Booth (2004)).

[17] Working memory measures the ability to retain and manipulate information. For example, 2nd-grade children were asked to remember increasingly long strings of numbers and repeat them in order and then backward. Cognitive flexibility refers to the ability to shift attention between tasks and adapt to different rules. For example, 1st-grade children were shown picture cards featuring trucks or stars, in red or blue, and were first asked to sort the cards by *shape* (trucks versus stars) and then by *color* (red versus blue). Inhibitory control refers to the capacity to suppress impulsive responses. For example, Kindergarten children were quickly shown a series of flashcards displaying either a sun or a moon and were asked to say "day" when they saw the moon and "night" when they saw the sun.

problems, among other classroom tasks. More importantly, these skills have been shown to predict long-term outcomes in adulthood related to labor market success, health and crime (Moffitt et al., 2011). We compute scores for each of the three domains, as well as an overall score.[18]

In 1st grade, we collected measures of happiness and effort. For happiness, we asked children whether they were always, sometimes, or never happy at school and in their classroom. Similarly, for effort, we asked whether they always, sometimes, or never made an effort to understand what their teachers were teaching and to learn as much as possible in school. Most children provided consistent responses to both questions. We aggregated the responses to construct two self-reported dummy variables: (i) children who were always happy and (ii) children who always put in effort.

In 6th grade, we collected data on child depression, self-esteem, growth mindset, and grit. To measure depression, we used the Patient-Reported Outcomes Measurement Information System (PROMIS) Depression Scale for children aged 11-17, developed by the American Psychiatric Association. We selected five questions from the National Longitudinal Study of Adolescent to Adult Health (Add Health) to measure self-esteem. For growth mindset, we chose 10 questions from the Dweck "Mindset Quiz"; growth mindset refers to the belief that intelligence is malleable and can be developed with effort(Blackwell et al., 2007). Finally, to measure grit, we adapted four questions from the 8-item Grit Scale for children (Duckworth and Quinn, 2009); grit refers to the ability to persevere at a given task. For each outcome, we aggregated responses using factor analysis. Further details on the child assessments and the IRT are provided in Appendix C.

Most of the tests were administered individually by specially trained enumerators. The only exception is some tests in 4th through 6th grades, which were administered in a group

[18]Unlike math test scores, we cannot aggregate questions using factor analysis since some tests are timed. For instance, in one task, children have 2 minutes to find as many sequences of "dog", "house", and "ball" in that exact order on a sheet with rows of dogs, houses, and balls in various possible sequences. The score on this test is the number of correct sequences the child finds. Therefore, we calculate separate scores for working memory, inhibitory control, cognitive flexibility, and a total executive function score, with each domain given equal weight.

setting by trained enumerators. All tests, except for the non-cognitive tests in 6th grade, were conducted at school. Prior to the official testing, a pilot study was conducted to select appropriate questions based on difficulty and discrimination parameters derived from an Item Response Theory (IRT) procedure. We selected questions that were easily comprehensible to the children based on their context and exhibited sufficient variability in the pilot study to capture the full distribution of students' ability.

2.3.2 High Achievers Information

At the end of each grade, we asked teachers to identify five students with the highest learning.[19] Teachers did not have access to any test results from the experiment and had to rely solely on their own knowledge of students' academic performance. Therefore, our analysis captures the behaviors and characteristics teachers associate with high learning. To mitigate concerns about subjectivity in these rankings, we classify a student as a high achiever if at least 50% of the teachers who observed them in previous grades identified them as such.[20] This approach implies that the definition of a high achiever may evolve over time as students are evaluated by more teachers. Some students may cease to be identified as high achievers, while others may begin to be recognized. By aggregating multiple, independent evaluations, this procedure reduces measurement error from any single teacher assessment, or from individual teacher behavior toward particular students, and provides a stronger signal of student performance in later grades.[21] Using this information, we construct the leave-one-out proportion of high achievers in each classroom.

There are several alternative ways to identify high achievers. For instance, one could

[19] Importantly, we did not ask teachers to identify top and bottom performers separately in math and language.

[20] For example, a child in 4th grade identified as having the highest learning by three former teachers would be considered a high achiever for that year. More importantly, teachers appear only once in our sample and are not allowed to teach in a future grade.

[21] Given concerns about potential gender bias, Apprendix Table A.1 shows that female and male students identified as high achievers are similar in baseline characteristics. This suggests that teachers apply similar criteria when identifying high-achieving students of different genders. Futhermore, our main results hold when using alternative definitions of high achievers based on test scores as discussed in Section 4.2.

use measures of innate ability (e.g., IQ scores), baseline characteristics (e.g., PPVT scores), parental education (Cools et al., 2022), or placement exam results (Busso and Frisancho, 2021). However, we rely on teachers' rankings to define high achievers for three main reasons. First, this approach enables us to identify high achievers dynamically each year—something that pre-experiment measures do not consistently allow. While baseline scores may provide valuable insights, they are not available for all children in the sample. For example, PPVT scores, though informative, are available for only about 14,000 of the nearly 28,000 students in our sample. Second, because tests in each subsequent grade incorporate both previously asked and new questions, they induce serial correlation in test scores over time, which could mechanically classify students as high achievers across multiple years. Finally, teacher rankings reflect classroom performance rather than performance on standardized tests, allowing them to serve as a distinct measure of "ability". Teachers may also value other characteristics beyond academic performance (e.g., persistence, grit) that would not be captured by test scores or other measures.

Nevertheless, relying on teachers' rankings to define high achievers presents some challenges. First, a key requirement for our empirical strategy is that the definition of high achievers does not suffer from reflection problems (Manski, 1993). In our context, teachers have information about the children when ranking them and can compare students within the same classroom, which could potentially bias their selection of the five highest-performing students. To mitigate this concern, we rely only on information from teachers in previous grades and do not use any data from the current grade that could be affected by reflection issues. Second, the probability of being designated as a high achiever is higher in smaller classrooms. To address this, we aggregate information from multiple teachers across different grades, which helps smooth out any idiosyncratic variation due to class size. Moreover, our empirical strategy compares students across classrooms within the same school-grade. Due to the experimental design, classroom sizes within a school-grade are very similar, so the probability of being identified as a high achiever should also be comparable across classrooms.

2.3.3 Teacher and Classroom data

We use the Classroom Assessment Scoring System (CLASS) (Pianta et al., 2015) to measure teacher behaviors based on recordings of classroom interactions over the course of an entire school day. The CLASS measures teacher behavior across three domains: Emotional Support, Classroom Organization, and Instructional Support.[22] Within each domain, there are three to four CLASS dimensions, each rated on a scale of 1 to 7. The CLASS protocol provides coders with specific guidance for assigning scores, categorizing them as "low" (1–2), "medium" (3–5), or "high" (6–7). The behaviors coders assess within each dimension are clearly defined and highly specific.

The CLASS has been widely used for research and policy purposes in the U.S., especially in preschool settings. For instance, Head Start grantees in the U.S. are required to achieve a minimum score on the CLASS to be re-certified for funding. The CLASS has also been employed as a measure of teacher quality in Latin America, including earlier work in Ecuador Araujo et al. (2016), Chile (Bassi et al., 2020; Yoshikawa et al., 2015) and Peru (Araujo et al., 2019). All Kindergarten through 4th-grade teachers were filmed for a full day (from approximately 8 a.m. to 1 p.m.) without prior notice. Teachers were informed of the filming only on the day itself, ensuring that the videos captured typical, planned interactions with students. Each classroom has only one teacher that teaches the same class during the calendar year, without a classroom aide, who was responsible for all academic subjects (exluding physical education, art and music when available). We strictly adhered to CLASS protocols when coding the footage. Each video recording was divided into 20-minute segments, with two coders evaluating each segment.[23] Further details on the CLASS dimensions, the scoring protocol, and its application in Ecuador are provided in Appendix D.

[22] Emotional Support measures how teachers promote a positive classroom climate and respond to students' emotional needs. Classroom Organization refers to the routines and procedures teachers use to manage students' behavior, time, and attention. Instructional Support evaluates how effectively teachers promote students' thinking through their implementation of the curriculum.

[23] In cases where the two coders provided significantly different scores, a third coder was assigned to evaluate the teacher. The inter-coder relability was approximately 0.92, suggesting that measurement error due to from substantial differences across coders was relatively low.

One disadvantage of the CLASS is that it is not a cardinal scale, which means it cannot be use directly as an input in the production function, unlike value-added, experience, and other teacher characteristics. However, previous studies have found that teacher behaviors, measured by the CLASS, are associated with higher test scores (Araujo et al., 2016). Following Araujo et al. (2016), we use the CLASS as a measure of Responsive Teaching. We categorize teachers into two groups (low and high quality) based on their CLASS scores, separately for each domain and for the total score.

2.4 Descriptive Statistics and Preliminary Checks

Table 1, Panel A provides summary statistics for the children in the sample. On average, children were five years old on the first day of Kindergarten, with 60% having attended preschool, and half being girls. The average score on the vocabulary skills (PPVT) test is 83 points, with a considerable range from 55 to 145. Furthermore, 90% of the children self-report being happy, and 85% report putting in effort. Thirteen percent of children are classified as high achievers by their previous teachers. Table 1, Panel B presents information on household and parental characteristics. The average age of mothers is 30 years and 34 years for fathers, with both having completed approximately 8.5 years of education. Regarding household conditions, 83% report having piped water, and 43% have a toilet at home.

Table 1, Panels C and D present classroom and teacher characteristics, respectively. On average, 15% of a student's peers in a given classroom are classified as high achievers based on teacher rankings, and the average classroom size is 37 students. However, these proportions vary significantly across classrooms, ranging from 0% to 57%. The average teacher in the sample has 18 years of experience. Additionally, 80% are tenured, and 84% are women. Importantly, teacher quality, as measured by the CLASS, varies across classrooms in each assessment domain.

Before estimating the impacts of high achievers on cognitive and non-cognitive skills, we provide descriptive evidence regarding the variation in the proportion of high achievers,

their characteristics, and potential estimates. First, the experiment generates considerable variation in exposure to high achievers. Appendix Figure A.1 illustrates the distribution of the proportion of high achievers in classrooms across all grades. Although only 13% of the children in the sample are classified as high achievers, most of them are distributed across different classrooms. In fact, more than 60% of the classrooms had three or more high achievers. As a result, only 26 classrooms did not contain a high achiever.[24]

Second, one potential concern with our preferred measure of high achievers is whether teachers can effectively identify them. Table 2 provides summary statistics of the characteristics of the children in our sample, comparing those classified as high achievers, based on the teacher's rankings from previous grades, with those who are not. The table shows that children classified as high achievers have higher math and executive function scores, as well as higher baseline vocabulary test (PPVT) scores. They are more likely to be female and report higher levels of happiness and effort. Overall, there are notable differences in socioeconomic status between high achievers and other children; for instance, high achievers tend to have more educated parents and are more likely to have attended preschool. There are no significant differences in the remaining socioeconomic variables. This suggests that teachers appear to identify high achievers correctly, at least based on their observable characteristics, while also considering other relevant characteristics.

Finally, Figure 1 illustrates the relationship between the (leave-one-out) proportion of high achievers and math test scores, conditional on the school-by-grade fixed effects. Specifically, it compares students who attend the same school but were exposed to different proportions of high achievers due to random assignment, without considering other factors like ability or gender. The figure suggests that children exposed to more high achievers obtained lower math test scores.

[24]This corresponds to 17 classrooms in 1st grade, 0 in 2nd grade, 1 in 3rd grade, 1 in 4th grade, 5 in 5th grade, and 2 in 6th grade.

3 Empirical Strategy

3.1 Main Model

The goal is to estimate the impact of a child's peer composition on her subsequent learning in elementary school. The dataset allows us to construct measures of the (leave-one-out) proportion of high achievers, as well as peers' lagged and current achievement, for children in 1st through 6th grade. With these data, we can investigate the effects of peer composition in both the short and medium-run. We use unique data on student rankings provided by teachers. As previously explained, a child is classified as a high achiever if at least 50% of the teachers who observed them in previous grades identified them as such. Therefore, to estimate the effect of high achievers on cognitive and non-cognitive skills, we estimate the following model pooling observations from all grades:

$$y_{icst} = \beta_1 FracHighAchievers_{cst} + \mathbf{X}_{icst}\alpha + \delta_{st} + \varepsilon_{icst} \tag{1}$$

where y_{icst} is one of students' i performance (measured by the corresponding test score) in classroom c in school s at the end of grade t. $FracHighAchievers_{cts}$ is the leave-one-out proportion of high achievers peers when the student is randomly assigned to classroom c in school s at grade t. This variable equals the proportion of students who are high achievers from the school-grade-classroom distribution of students after eliminating student i from the distribution. δ_{st} is a school-by-grade fixed effects. $\mathbf{X}_{icst}$ is a vector of individual-level controls such as children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. We cluster standard errors at the school-by-grade level, which allows students' outcomes in different classrooms to correlate within schools on a given grade. The parameter of interest, β_1, measures the impact of the (leave-one-out) proportion of high-achievers on the test scores.

Previous literature has found that how girls and boys respond to high achiever peers

depends on the gender of those high achievers (Busso and Frisancho, 2021; Cools et al., 2022). We explore this question by analyzing how test scores differ for girls and boys when they are exposed to high-achieving peers, separated by gender. Therefore, we estimate the following model:

$$y_{icst} = \beta_1 MaleFracAchievers_{cst} + \beta_2 FemaleFracAchievers_{cst} + \mathbf{X}_{icst}\alpha + \delta_{st} + \varepsilon_{icst} \quad (2)$$

where $MaleFracAchievers_{sct}$ ($FemaleFracAchievers_{sct}$) are the leave-one-out proportion of high achievers male (female) peers in classroom c at grade t in school s. Specifically, they are the proportion of students from the specific gender-school-grade-classroom distribution of students after eliminating student i from it. The parameters of interest, β_1 and β_2, measure the impact of the (leave-one-out) proportion of male and female high-achievers on the test scores, respectively

Identification

The empirical strategy exploits variation in exposure to high achievers across classrooms within the same school and grade, which is a common approach in the literature. The key identification assumption is that, conditional on school-by-grade fixed effects, classrooms with differing peer composition do not differ systematically along other dimensions. The school-by-grade fixed effects account for differences across cohorts within a given school and for school-grade characteristics that are constant across students. This key assumption is supported by the random assignment of students to classrooms at the beginning of each grade.

A potential concern is weak variation in peer composition, which can arise when estimating peer effects under random assignment to classrooms (Angrist, 2014). This issue is particularly relevant in settings with large peer groups, where randomization may produce limited variation. In our context, the variation in the proportion of high achievers decreases

with class size, and identification relies on residual variation due to finite-sample imbalances in classroom assignments. However, this concern is mitigated in our setting, as most classrooms have fewer than 45, with an average of 37.

However, recognizing these potential concerns, we conduct four diagnostic analyses to assess the extent of variation in the proportion of high achievers and to test for random assignment. First, we assess whether the number of high achievers per classroom follows a hypergeometric distribution with school-specific parameters. Figure 2 shows the distribution of the standardized deviations between the observed and expected number of high achievers under this distribution. Only 8.2% of classrooms have a number of high achievers that lies outside the 95% confidence interval implied by the hypergeometric distribution. Morover, the 90th and 10th percentiles of the observed distribution are 7 and 2, compared to expected values of 6.7 and 2.9, respectively. These results suggest that the observed variation in peer composition is consistent with theoretical expectations under random assignment.

Second, the ability to exploit peer composition relies on sufficient residual variation in the key variables after accounting for fixed effects. Given the random assignment, the distribution of the proportion of high achievers in a given classroom, conditional on school-by-grade fixed effects, should be approximately normal. Appendix Figure A.2 shows that the distribution of the residualized proportion of high achievers across classrooms is indeed approximately normal, consistent with random assignment. This suggests that variation in peer composition is likely arbitrary. More importantly, the figure also shows some within school-grade variation in the proportion of high achievers, further supporting the validatity of our empirical strategy.

Third, to obtain precise estimates, there must be sufficient variation in the leave-one-out proportion of high achievers after controlling for school-by-grade fixed effects. Appendix Table A.2 reports the variation in this proportion before and after including the fixed effects. As expected, including the fixed effects reduces the standard deviation by approximately 30 percent. Nevertheless, the remaining variation is substantial, suggesting that there is

sufficient identifying variation to credibly estimate the effects.

Finally, we test whether the variation in the proportion of high achievers within a school-grade is consistent with random assignment by comparing the actual distribution to a simulated one. To this end, we conduct Monte Carlo simulations in which students are randomly assigned to classrooms within the same school and grade. Following Bietenbeck (2020), we take the number and size of classrooms, as well as the number of high achievers per classroom, using the observed data. In the simulated dataset, we regress the proportion of high achievers on school-by-grade fixed effects and collect the residuals. Appendix Figure A.3 plots the distribution of these residuals from 1,000 replications alongside those from the observed data. The two distributions are visually similar, which is consistent with random assignment and further supports the assumption that high achievers were randomly assigned to classrooms within school-grades.

Nevertheless, to further support the causal interpretation of the estimates, we provide several sensitivity tests. First, sensitivity tests are conducted for different ways of controlling for differences across schools and grades and to address any concerns regarding omitted factors influencing the results. Specifically, we estimate three alternative specifications: i) we exclude the grade fixed effect; ii) we include separate school and grade fixed effects; and (iii) we include teacher controls to account for the possibility that teachers may influence the classroom environment and affect student outcomes. As we show later, the results from these specifications are similar to those obtained using the main specification.

Second, we test the sensitivity of the estimates to different ways of defining who is classfied as a high achiever in the classroom. For our preferred measure, we estimate three new proportions by classifying a child as a high achiever if at least 25%, 75%, or 100% of the teachers who observed them in previous grades identified them as such, instead of the original 50%. We also create a new measure of high achievers using only the information from the previous year's teacher, instead of using information from all teachers. Given the availability of test scores, we also construct two measures based on the children's performance: (i)

whether a student is above the 95th percentile of the corresponding test score from the previous year, and (ii) whether a student is above the 95th percentile of the baseline PPVT test. The results show no significant changes.[25]

Third, we test the sensitivity of the estimates to the exclusion of one school at a time to ensure that the results are not driven by a single school in a given grade. Appendix Figure A.4 shows the distribution of the leave-one-out coefficient estimates. In particular, one unique regressions was estimated following our preferred specification, omitting one school-grade in each iteration. The figure suggests that the results are not driven by one particular school-grade. Indeed, the distribution is very tight and centers around the value of the coefficient found in the main analysis.

Finally, we analyze whether having a higher proportion of high achievers increases the probability that a child attrits from our school sample between grades. A potential concern is that differential attrition could present an estimation challenge. Appendix Table E.4 shows the impact of the leave-one-out proportion of high achievers on the likelihood of leaving the sample between two consecutive grades. The table shows that children are no more likely to attrit when exposed to a higher proportion of high achievers. Therefore, we find no evidence of selective attrition. Nevertheless, in Appendix Table E.5, we restrict our sample to the balanced panel of children and estimate the main equation. We find that the results are similar.

3.2 Dynamics

Due to the uniqueness of the data, we can study the dynamics of peer effects and how they accumulate over time. For this, we estimate the following specification:

$$y_{isc,t+l} = \beta_1 FracHighAchievers_{sct} + \mathbf{X}_{isct}\alpha + \delta_{st} + \varepsilon_{isct} \tag{3}$$

[25] We also use the parents' education to construct a proportion of high achievers, similar to the approach used by Cools et al. (2022). Appendix E shows that the results are consistent with those obtained using the preferred definition.

where $y_{isc,t+l}$ is one of students' i performance (measured by the corresponding test score) at the end of grade $t+1$. We estimate these regressions for every grade (1st grade to 6th grade). When $l = 0$, equation 3 is equivalent to equation 1 and provides estimates of the short-run (contemporary) effects of peer composition at grade t, $FracHighAchievers_{sct}$, on learning at the end of that same grade, y_{isct}. We label this effect as $\beta_{t,0}$. When $l > 0$, equation 3 provides estimates of the medium-term effects of peer composition at various lags (at most 6 for Kindergarten), which we label $\beta_{t,l}$

4 Results

4.1 Main Results

We estimate the regression model specified in Equation 1 separately for each cognitive and non-cognitive test score. Table 3 shows that a higher proportion of high-achieving peers reduces scores in math and executive function tests. For instance, a one standard deviation increase in the leave-one-out proportion of high achievers reduces math test scores by 0.011 SD. Similarly, an increase of one standard deviation is associated with a 0.014 standard deviation decrease in executive function scores.[26] These results are surprising given the previous literature on high-achieving peers, which generally finds positive effects. However, they are consistent with the findings of Hoxby and Weingarth (2005). In terms of magnitude, the effects are slightly smaller than the 0.04SD decrease in GPA found by Chen and Hu (2024). Their estimates, however, focus on high-ability students, which may explain the difference, as we discuss later.

There are three plausible explanations for our findings. First, the presence of high-achieving peers may lower the relative academic rank of other students within the classroom.

[26] Appedidx Table A.3 shows the results for each of the components included in the math and executive function tests. It indicates that the proportion of high achievers negatively affects all components of math, with stronger effects on number sense and word problems. In the executive function components, only cognitive flexibility and working memory are negatively affected, while inhibitory control is not.

Students who are pushed down to a lower rank in the local distribution may reduce their effort or lose self-confidence, which can negatively affect their performance, as documented in tracking settings (de Roux and Riehl, 2022). Second, the presence of high achievers may intensify competition, which could negatively impact students' mental health, motivation, and stress levels, in line with previous evidence on the effects of competition in education (Chen and Hu, 2024). Finally, teachers may focus more attention on high achievers and neglect others students, or they may adjust their teaching strategies and classroom management, potentially mediating the effects on learning outcomes.

Given the asymmetric gender effects of peers found in the literature, Figure 3 shows that, on average, the coefficients for the proportion of male high achievers tend to be larger in magnitude than those for females, although the differences are not statistically significant. The figure also illustrates how the share of female and male high achievers affects male and female students separately. Interestingly, the results suggest that the proportion of male high achievers affects only male students, while the proportion of female high achievers only female students. These findings are consistent with some of the results in Lavy et al. (2012), who found that high-achieving male peers negatively impact boys, and they suggest that crowding out in top-tier activities may drive these effects.

These findings may seem unexpected considering that Busso and Frisancho (2021) and Cools et al. (2022) find that male students negatively affect female ones. However, it is important to note that those studies focus on middle and high school students, where interactions between males and females are more common. This could explain why males have an impact on females in those contexts. In contrast, our study uses a sample of elementary school children, during which female students tend to befriend other females, and male students with other males (McPherson et al., 2001; Garrote et al., 2023). Indeed, in our sample, 89.6% of males report having a male best friend and 92.7% of females report having a female best friend. Moreover, around 19% of the children have friends of the opposite gender. This behavior could explain why the effects are concentrated mostly within gender,

as same-gender friendship networks are more common during these years.

One potential concern is mean reversion, where children who initially score lower might experience larger increases in the next grade, while those with higher initial scores could experience declines. However, given that teachers identify high achievers without knowing their test scores, mean reversion is unlikely to explain our results for two reasons. First, our preferred measure of high achievers relies on rankings provided by multiple teachers, not just one, so no explicit design allows teachers to strategically adjust who is considered a high achiever. Second, as explained before, teachers, on average, do not make mistakes when identifying high achievers. Moreover, Appendix Figure A.6 shows no evidence suggesting that teachers across grades differ their ability to identify higher-achieving students. The distribution of test scores for high achievers is consistently to the right of that for non-high achievers.

However, recognizing that there could be a mechanical reason for why test scores might decrease, we address mean reversion by analyzing changes in the distribution of children at the top end. Over the sample period, math test scores exhibit some mean reversion: children who were in the top 20% of scores the previous year experience a 9 percentile decrease in their math scores in the current year. This is slightly higher than the 5 percentile decrease observed in Lavy et al. (2012). Nevertheless, random assignment should have balanced out any differences in test scores. Therefore, conditional on ability and being above the 80th percentile, children should be similarly affected by mean reversion, regardless of peer composition, particularly the proportion of high achievers. Indeed, when dividing the top quintile into 20 percentiles, the decrease ranges from 7 to 10 percentiles, with most clustered around 9. Therefore, it is unlikely that statistical or incidental mean reversion explains our results.

4.2 Robustness checks and Alternative Specifications

This section provides a brief summary of several alternative specifications and robustness checks to address concerns about the main specification. The first three specification checks test whether the results are robust to different ways of controlling for differences across schools and grades. The first check excludes the grade fixed effect and includes only the school fixed effect. The second check includes school and grade fixed effects separately. Finally, the last specification check includes teacher controls to account for how teachers may influence the classroom environment and affect student outcomes through their interactions. Figure 4 presents the results of these alternative specifications checks. Following the main result (i.e., the main specification), the next three estimates demonstrate the insensitivity to the choice of fixed effects.

The next robustness checks test the sensitivity of the estimates to different ways of defining who is classified as a high achiever in the classroom. First, our preferred measure uses information from all the teachers in previous grades and classifies a child as a high achiever if at least 50% of the teachers who observed them in previous grades identified them as such. However, given that this cutoff was chosen arbitrarily, we check how robust the results are to the use of other cutoffs. Second, we construct a proportion of high achievers using information from only the previous grade teacher, rather than from all the previous teachers. The next four estimates in Figure 4 show the main specification using cutoffs of 25%, 75%, and 100%, and using the previous grade teacher only, respectively. The four coefficients show that the estimates are not sensitive to the choice of cutoff.

Finally, we analyze the sensitivity of the results to constructing the proportion of high achivers using test scores. We construct two different measures: (i) whether a student is above the 95th percentile of the corresponding test score from the previous year, and (ii) whether a student is above the 95th percentile of the baseline PPVT test. The last two coefficients in Figure 4 show the results for these measures. The coefficient using the previous year's test score shows similar results, while the one using the PPVT score is similar

in magnitude but not statistically significant. However, this coefficient should be interpreted cautiously, as the PPVT was collected only at the baseline, and new entrants do not have information on this test. Additionally, since the PPVT is a vocabulary test rather than a math test, this could explain the absence of effects on math scores.

4.3 Dynamics

We estimate the dynamics of the effects by estimating the regression of peer composition separately for children in each grade (1st grade to 6th grade), both contemporaneously (without lags, as in equation 1 above) and at various lags (up to 5, as in equation 3). Table 6 presents the results for the proportion of high achievers in math. Column (1) shows that the short-term effects of the proportion of high achievers on math scores are negative only for 1st grade.

Regarding the evolution over time of the effects, in columns (2) through (5), we report estimates of the effect of the proportion of high achievers on math achievement after (up to) 1, 2, 3, 4, and 5 lags, respectively. In the first row, corresponding to peer composition in 1st grade, the coefficient in column (2) represents the impact of peer composition in 1st grade on second-year scores, while column (3) represents the impact of peer composition in 1st grade on third-year scores. These coefficients are relatively stable and statistically significant. However, in contrast to previous evidence on ranking (Carneiro et al., 2025), the effects over time decline. Interestingly, the table suggests that only 1st grade matters, and peer composition during this early grade appears particularly relevant. These results align with previous evidence on how Kindergarten experiences have long-term consequences (Rury, 2025). Similarly, Table 7 presents the results on executive function, showing similar findings to math test scores for 1st grade, but also indicating effects in subsequent grades. These results suggest that exposure to high achievers has long-term effects on executive function, a set of skills related to a child's ability to plan, focus attention and remember instructions.

4.4 Potential Mechanisms

Having shown that the proportion of high achievers negatively affects test scores in both cognitive (math and executive Function) skills, we now explore potential mechanisms that might explain these results. We focus on three main channels: (i) the classroom environment, (ii) the effects on other outcomes (non-cognitive skills, happiness, and effort), and (iii) the role of teacher quality.

4.4.1 Classroom Environment

In this section, we explore the roles of competition, relative ranking, and classroom environment behind the observed negative peer effects. First, we examine heterogeneity by previous achievement to test whether the effects are concentrated among students at the top of the distribution. Second, we assess whether these effects are driven by changes in classroom rank. Third, we estimate non-linear effects in exposure to high achievers, which may imply increasing competitive pressure. Fourth, we analyze heterogeneity by school size as a proxy for differences in classroom environment. Overall, we find that negative peer effects are more pronounced in environments with heightened competition, increased peer interaction, and stronger awareness of relative ranking, though we cannot conclusively distinguish between these mechanisms.

In our context, children with higher prior-year scores are more likely to experience downward shifts in relative rank. Figure 5 divides the sample into quintiles based on prior math scores and shows that negative peer effects are concentrated in the top quintile. This is consistent with the "Invidious Comparison Model", which predicts stronger effects among students near the top of the distribution. These findings also align with prior literature showing that high-achieving students tend to be more competitive than their lower-achieving peers (Syeda and Khalid, 2012), and that high-ability students are particularly negatively affected by the presence of other high achievers due to intensified competition among them (Chen and Hu, 2024).

The presence of high achievers could push some students down in the classroom rank distribution, which may reduce effort or self-confidence. Since classroom rank has positive effects on student outcomes in this setting (Carneiro et al., 2025), we estimate models that include both classroom rank and the proportion of high achievers. Table 8 shows that, for the full sample, the effect of peer composition is statistically not significant once rank is accounted for. However, among students in the top quintile of prior performance, the proportion of high achievers still has a negative effect even after controlling for rank. In particular, Column 4 shows negative effects even when comparing two children with the same classroom rank but exposed to different proportions of high achievers. Appendix Figure A.5, which includes rank in a non-linear way, shows that both peer composition and rank independently shape student outcomes, particularly among top performing students. While Carneiro et al. (2025) highlight the importance of rank effects, our findings suggest that peer composition also affects test scores.

To estimate the non-linear effects of peer composition, we create quintiles based on the proportion of high achievers in the classroom. Figure 6 shows that negative effects on test scores emerge only in the upper two quintiles. Being in a classroom with fewer than three high achievers has little impact, but being in a classroom with more appears detrimental. This pattern suggests that competition may play a role, as students might feel increased pressure to perform or experience crowding-out effects due to limited opportunities for top-tier activities or recognition. Overall, these results indicate that the additional competition produced by an increase in the proportion of high achievers negatively impacts test scores.

Furthermore, we estimate effects by school size, using the average number of students per school over the seven years of the experiment. We use the median to define small and large schools. We expect peer effects to be stronger in smaller schools as they are characterized by heightened competition, greater peer interaction, and increased salience of relative class rank. Figure 7 shows that the detrimental effects are concentrated in smaller schools, with estimates for small and large schools statistically different. However, as discussed earlier,

variation in peer composition decreases with class size. Therefore, the greater variation observed in smaller schools could increase the likelihood of detecting effects.

Finally, we analyze the interaction between peer composition and school size. Appendix Figure A.7 shows that the non-linear effects are more pronounced in small schools (Panel A), but are not detectable in larger schools (Panel B). In particular, students in small schools exposed to the highest proportions of high achievers experience the largest declines in test scores. These findings reinforce the idea that the classroom environment mediates the effects, though we cannot conclusively identify the underlying mechanism.

4.4.2 Effects on other outcomes

In the previous section, we show that peer effects are mediated by classroom environment. In this section, we explore how high achievers affect other outcomes, particularly mental health, non-cognitive skills and motivation. First, Table 4 shows no significant effects on mental health outcomes and non-cognitive skills, such as depression, self-esteem, grit, and growth mindset in 6th grade. However, these estimates should be interpreted cautiously, as the smaller sample size leads to noisier estimates, and our power to detect effects is reduced.

Now, we turn to self-reported measures of happiness and effort. One potential explanation for the test scores results is that children feel less happy when the are exposed to more high achievers, leading them to put in less effort on their work and tests. If students exert less effort, the estimates of the effects on test scores would need to account for that. Table 5 shows that self-reported happiness levels decrease as the leave-one-out proportion of high achievers increases. However, this reduction in happiness is not accompanied by a decline in self-reported effort. Interestingly, Appendix Figure A.8 further shows that the decline in happiness is concentrated among students who were at the top of the distribution in the previous year. These results suggest that reductions in test scores could be attributed to decreased motivation. While we do not find evidence of reduced self-reported effort, the drop in happiness may reflect a decline in motivation or increased stress, which could affect

their performance. Together with the evidence on rank and peer composition, these results suggest that negative peer effects may partly operate through reductions in well-being and motivation, especially among top performing students.

4.4.3 Teacher Quality

Given the existing literature on teacher quality and its positive effect on test scores, we test whether teacher behaviors, as measured by the CLASS, can mitigate the negative peer effects. Panel A in Figure 8 shows that high-quality (those above the median) teachers can reduce the negative effects, although some detrimental consequences on math test scores remain. Panel B in the same figure examines the results by CLASS domain and illustrates that teachers who are high-quality in emotional support and classroom organization are the ones most capable of mitigating these effects. These findings suggest that teachers with better-planned classroom routines and structure may be better equipped to distribute attention more equitably and manage peer dynamics effectively. Overall, these results highlight the importance of teacher quality, highlighting the role of classroom management in shaping peer effects on test scores.

5 Conclusion

This paper analyzes the impact of peer and gender composition on students' cognitive and non-cognitive skills in elementary school settings. The data come from a unique longitudinal experiment in Ecuador where children are randomly assigned to classrooms at the beginning of each school year for seven consecutive years. This random assignment implies that the proportion of high achievers in a classroom within a school is random. Compliance with the random assignment was nearly perfect, averaging 98.9% over the seven years. Notably, in our data, two students with the same underlying ability who attend the same school can experience different peer compositions because they are randomly assigned to different

classrooms, each with slightly different peers.

We find that exposure to high achievers can negatively affect test scores in cognitive skills, such as math and executive function. Moreover, these negative effects are stronger for students who were top performers in the previous year. The negative effects are more pronounced in classrooms with a higher proportion of high achievers and smaller classrooms, suggesting that environments characterized by heightened competition, increased peer interaction, and stronger awareness of relative ranking may play a significant role. However, no significant effects were observed on non-cognitive skills which suggest that future research should explore how high achievers impact non-cognitive outcomes. These findings contribute to the understanding of how peer and gender composition influence student outcomes during formative years. Finally, having higher-quality teachers can help mitigate the adverse effects on learning.

This research has several advantages compared to previous studies. First, we leverage the random assignment in elementary schools to analyze peer composition effects in a developing country in Latin America. This setting allows us to explore the variation in the proportion of high achievers in the classroom, overcoming any selection and reflection biases present in other peer effect studies. However, we also provide evidence addressing the concerns of weak variation when estimating peer effects under random assignment to classrooms. Second, we show that peer composition has long-term effects, though these effects decline over time. Our results highlight the importance of 1st grade peers, suggesting that peer composition in early grades is particularly relevant. Third, we explore both classroom environment and teacher quality as potential mechanisms behind the observed effects of exposure to high-achieving peers, providing insights into the complex dynamics in early educational settings.

Finally, given that peer effects are context-specific, these results raise essential policy concerns about how to address these adverse effects in Latin America and identify which policies work best. Future research should explore the underlying mechanisms through which exposure to high achievers affects test scores and identify ways to mitigate these effects,

either through optimal allocation of children to classrooms or by providing teachers with the necessary tools to address them.

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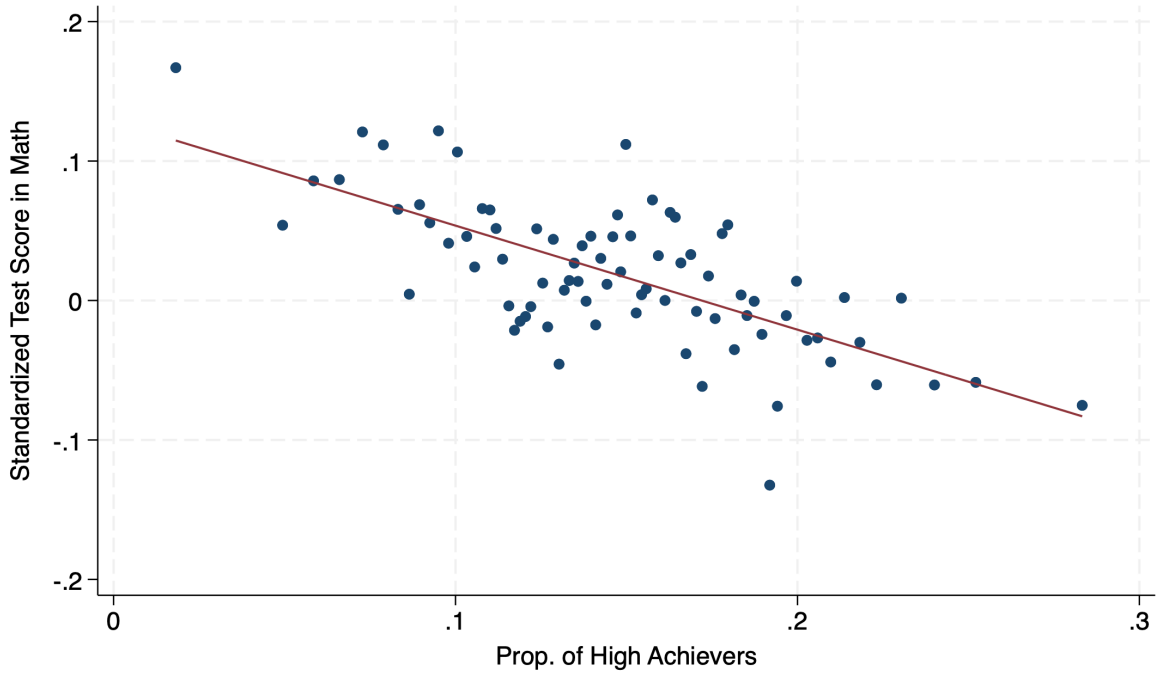
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6 Figures and Tables

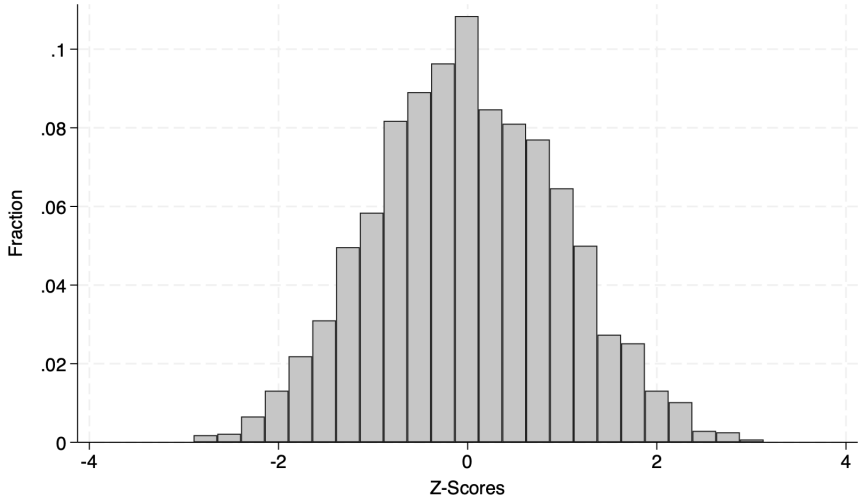
6.1 Figures

Figure 1: Correlation between Proportion of High Achievers and Cognitive Skills



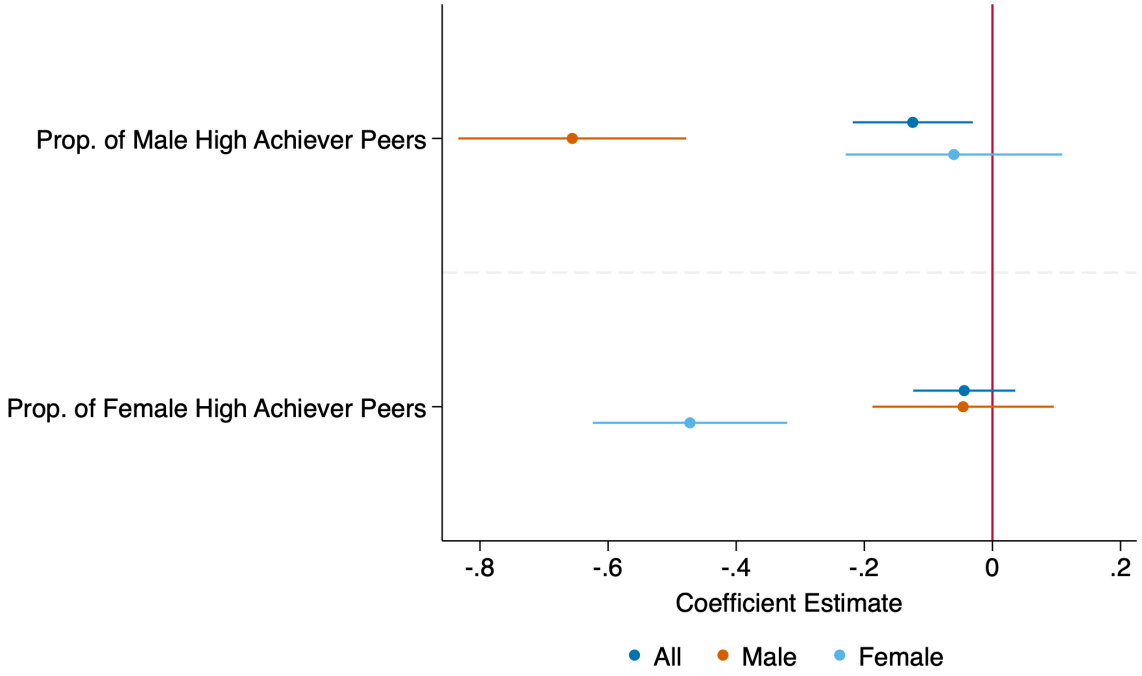
Notes: The figure above shows the relationship between the (leave-one-out) proportion of high achievers and math test scores. The plot does not include controls.

Figure 2: Distribution of Standardized Deviations from Hypergeometric Expected Number of High Achievers



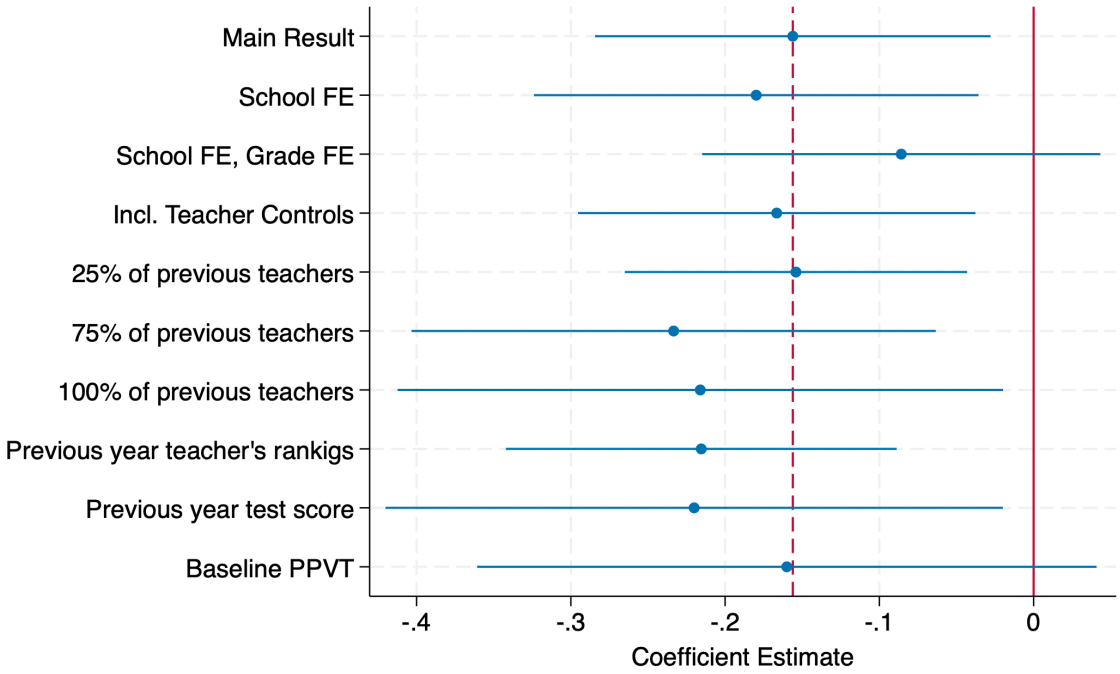
Notes: The figure above shows the distribution of the standardized deviations of the observed number of high achievers in the classroom from its expected value under the hypergeometric distribution with school-specific parameters.

Figure 3: Heterogeneous Effects of High Achievers on Math Scores by Gender



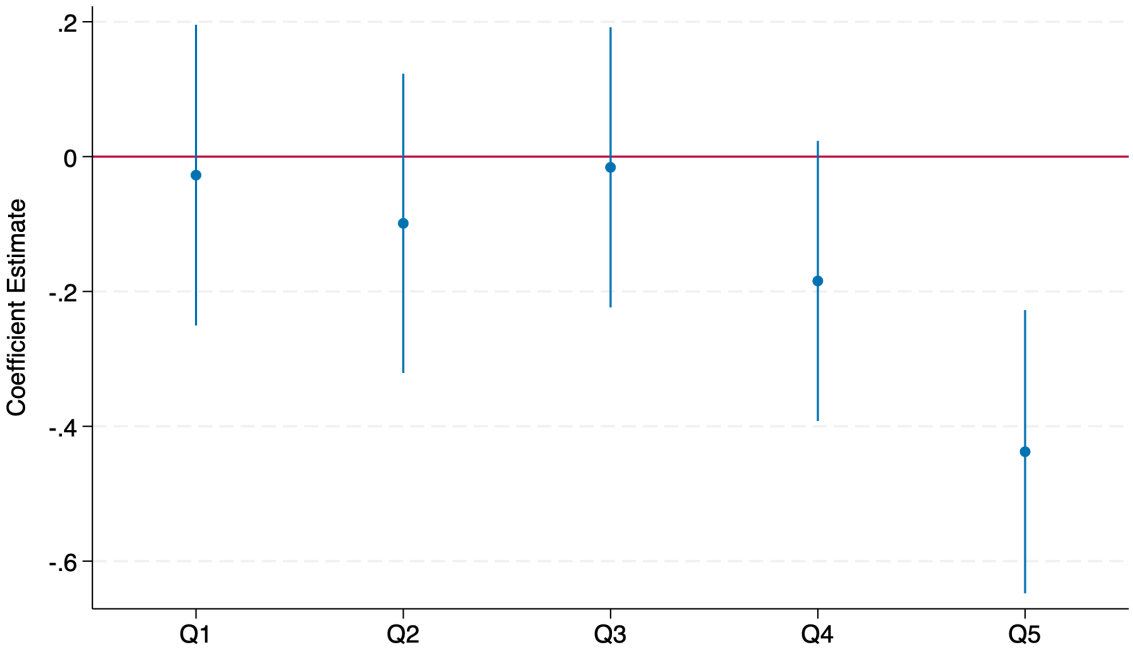
Notes: The figures above report estimates from regressions of the leave-one-out proportion of high-achiever peers separated by gender on math test scores separately for males and females. All regressions are limited to schools with at least two classrooms per grade. Horizontal bars represent 95% confidence intervals. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Figure 4: Robustness Checks on Math Scores



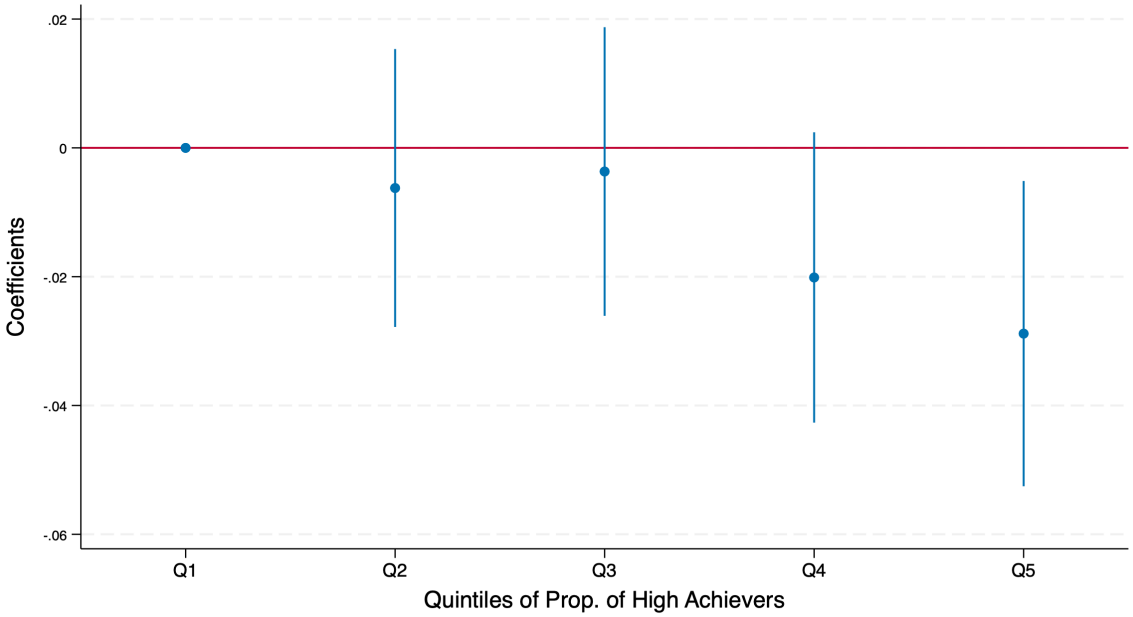
Notes: The figure above reports estimates from regressions of the leave-one-out proportion of high-achiever peers on math test scores. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. Horizontal bars represent 95% confidence intervals. Standard errors are corrected for heteroskedasticity and are clustered at the school-by-grade level. The "Main Result" estimate (at the top) uses the specification Table 3. All other estimates are variations on the baseline model. Estimates 2-4 vary the set of fixed effects and controls included. Estimates 5-7 use different cutoffs to define who is a high achiever using the teachers' rankings from teachers in the previous grades. Estimate 8 uses only the information from the previous teacher to define who is a high achiever. Estimate 9 uses the previous year test scores to define who is a high achiever, while estimate 10 uses the Baseline PPVT score to define who is a high achiever.

Figure 5: Heterogeneous Effects of High Achievers on Math Scores by Previous Test Results



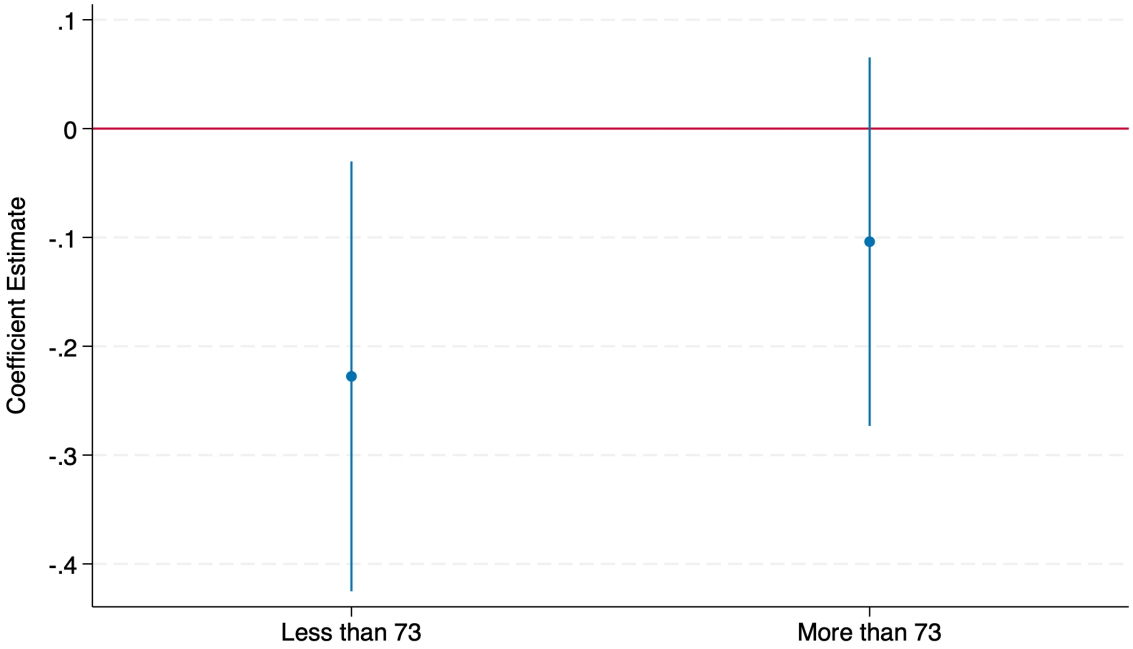
Notes: The figures above report estimates from regressions of the leave-one-out proportion of high-achiever peers on math test scores by quintiles of the test result in the previous year. All regressions are limited to schools with at least two classrooms per grade. Vertical bars represent 95% confidence intervals. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Figure 6: Non-Linear Effects of High Achievers on Math Scores



Notes: The figures above report non-linear estimates from regressions of the quintiles of the leave-one-out proportion of high-achiever peers on math test scores. All regressions are limited to schools with at least two classrooms per grade. Vertical bars represent 95% confidence intervals. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

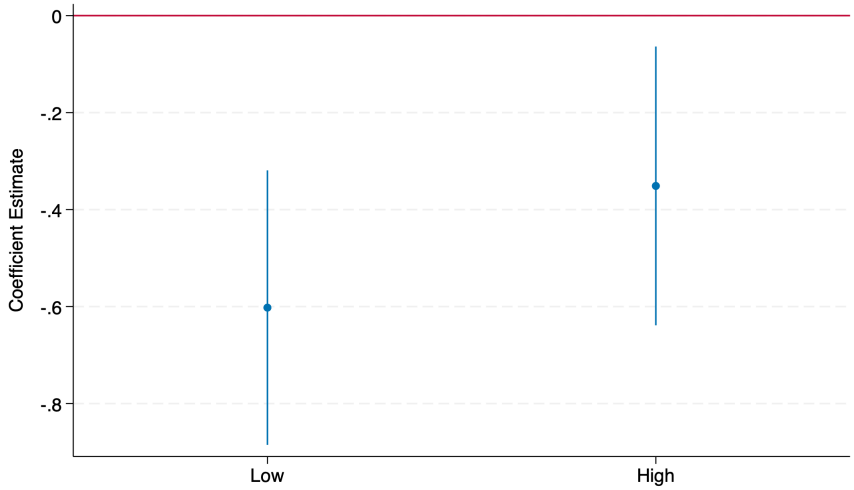
Figure 7: Heterogeneous Effects of High Achievers on Math Scores by School Size



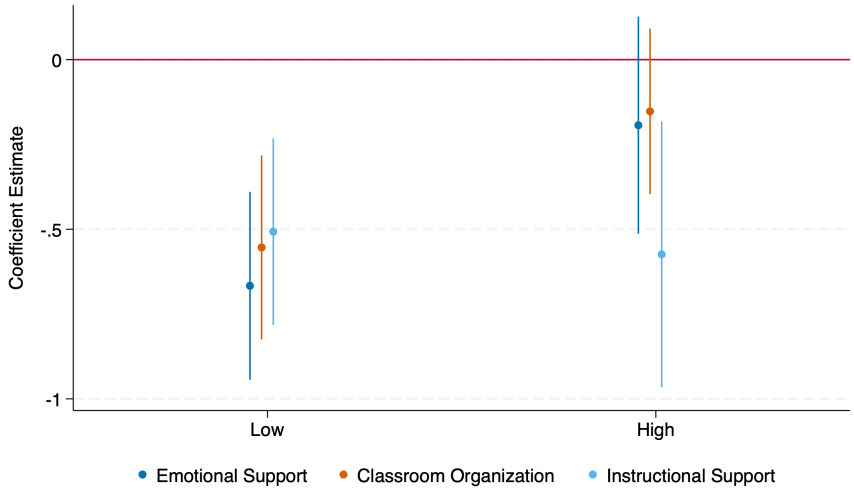
Notes: The figures above report non-linear estimates from regressions of the quintiles of the leave-one-out proportion of high-achiever peers on math test scores. Schools are separated into two groups: small and large, using the median size as the cutoff which corresponds to 73 students. All regressions are limited to schools with at least two classrooms per grade. Vertical bars represent 95% confidence intervals. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Figure 8: Heterogeneous Effects of High Achievers on Math Scores by Teacher Quality

(a) CLASS Score



(b) Components



Notes: The figures above report estimates from regressions of the leave-one-out proportion of high-achiever peers on math test scores by teacher quality measured using the CLASS *(Classroom Assessment Scoring System)* score. Teachers are separated into two groups: low and high quality, using the median score as the cutoff. All regressions are limited to schools with at least two classrooms per grade. Vertical bars represent 95% confidence intervals. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

6.2 Tables

Table 1: Child, Teacher, and Classroom Characteristics

	Mean	SD	Median	Min	Max
A. Child characteristics					
Age of child (in months) in 2012	60.30	4.94	60.00	32.00	142.00
Sex (1 = Female)	0.49	0.50	0.00	0.00	1.00
Receptive vocabulary score (PPVT)	82.89	15.87	81.00	55.00	145.00
High Achiever	0.13	0.34	0.00	0.00	1.00
Lagged Math Test Score	0.00	1.00	0.02	-3.83	3.58
Lagged Executive Function Test	0.00	1.00	0.05	-5.45	6.13
Self-reported Happiness	0.90	0.30	1.00	0.00	1.00
Self-reported Effort	0.85	0.35	1.00	0.00	1.00
Proportion who attended preschool	0.60	0.49	1.00	0.00	1.00
B. Household characteristics					
Mother's years of completed schooling	8.77	3.80	9.00	0.00	22.00
Father's years of completed schooling	8.50	3.83	8.00	0.00	22.00
Mother's age	30.22	6.57	29.00	5.00	93.00
Father's age	34.54	7.89	33.00	5.00	99.00
Household has piped water in home	0.83	0.38	1.00	0.00	1.00
Household has flush toilet in home	0.46	0.50	0.00	0.00	1.00
C. Classroom characteristics					
Class size	36.94	6.47	37.00	8.00	60.00
Prop. of High Achievers	0.15	0.07	0.14	0.00	0.57
D. Teacher characteristics					
Female	0.84	0.36	1.00	0.00	1.00
Years of experience	17.63	10.35	15.58	0.08	57.00
Prop. tenured	0.80	0.40	1.00	0.00	1.00
CLASS Score	-0.02	1.00	0.02	-4.29	4.28
Emotional Support Score	-0.02	0.99	-0.05	-4.98	4.89
Classroom Organization Score	-0.02	1.01	0.06	-5.36	2.58
Instructional Support Score	-0.02	0.98	-0.29	-1.03	7.10

Notes: Table reports summary statistics of the children in the sample. It includes children's characteristics and those of their assigned classrooms and teachers.

Table 2: Characteristics of high-achieving students

	Not High Achiever	High Achiever	Difference (1)-(2)
	(1)	(2)	(3)
A. Children characteristics			
Age of child (in months) in 2012	60.157	61.153	-0.996***
	(4.953)	(4.796)	(0.118)
Sex (1 = Female)	0.475	0.562	-0.087***
	(0.499)	(0.496)	(0.012)
Receptive vocabulary score (PPVT)	81.467	91.606	-10.140***
	(15.265)	(16.694)	(0.407)
Lagged Math Test Score	-0.154	0.922	-1.076***
	(0.943)	(0.816)	(0.008)
Lagged Executive Function Test	-0.108	0.633	-0.741***
	(0.977)	(0.892)	(0.009)
Self-reported Happiness	0.895	0.950	-0.054***
	(0.306)	(0.218)	(0.006)
Self-reported Effort	0.851	0.870	-0.018**
	(0.356)	(0.336)	(0.009)
Proportion who attended preschool	0.604	0.648	-0.043***
	(0.489)	(0.478)	(0.012)
B. Household Characteristics			
Mother's years of completed schooling	8.601	9.835	-1.234***
	(3.748)	(3.950)	(0.097)
Father's years of completed schooling	8.328	9.473	-1.145***
	(3.775)	(4.007)	(0.109)
Mother's age	30.144	30.656	-0.512***
	(6.560)	(6.618)	(0.163)
Father's age	34.495	34.748	-0.253
	(7.892)	(7.853)	(0.216)
Household has piped water in home	0.828	0.841	-0.012
	(0.377)	(0.366)	(0.009)
Household has flush toilet in home	0.455	0.473	-0.018
	(0.498)	(0.499)	(0.012)

Notes: Table reports summary statistics of the children in the sample. It includes children's characteristics and those of their household.

Table 3: Effects of High Achievers on Cognitive Skills

	Math	Executive Function
	(1)	(2)
Prop. of High Achiever Peers	-0.156**	-0.194**
	(0.065)	(0.081)
Mean of Dependent Variable	0.019	0.019
Treatment Effect of 1SD increase	-0.011	-0.014
Observations	87303	56626
Controls	Yes	Yes
School-by-grade FE	Yes	Yes

Notes: The table reports estimates from regressions of the leave-one-out proportion of high-achiever peers on cognitive skills. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Table 4: Effects of High Achievers on Non-Cognitive Skills

	Depression	Self-esteem	Growth Mindset	Grit
	(1)	(2)	(3)	(4)
Prop. of High Achiever Peers	-0.285	-0.057	-0.049	-0.136
	(0.258)	(0.254)	(0.262)	(0.236)
Mean of Dependent Variable	0.001	0.001	0.001	0.001
Treatment Effect of 1SD increase	-0.017	-0.003	-0.003	-0.008
Observations	7763	7763	7763	7763
Controls	Yes	Yes	Yes	Yes
School-by-grade FE	Yes	Yes	Yes	Yes

Notes: The table reports estimates from regressions of the leave-one-out proportion of high-achiever peers on non-cognitive skills. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Table 5: Effects of High Achievers on Happiness and Effort

	Happiness	Effort
	(1)	(2)
Prop. of High Achiever Peers	-0.098**	0.019
	(0.048)	(0.058)
Mean of Dependent Variable	0.903	0.854
Treatment Effect of 1SD increase	-0.008	0.002
Observations	12034	12034
Controls	Yes	Yes
School-by-grade FE	Yes	Yes

Notes: The table reports estimates from regressions of the leave-one-out proportion of high-achiever peers on cognitive skills. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Table 6: Cumulative Effects of High Achievers on Math Scores

	Lags					
	0	1	2	3	4	5
	(1)	(2)	(3)	(4)	(5)	(6)
1st grade	-0.521**	-0.172	-0.227**	-0.128	-0.155*	-0.150*
	(0.205)	(0.120)	(0.112)	(0.107)	(0.0911)	(0.0851)
2nd grade	-0.077	-0.121	-0.133	-0.130*	-0.066	
	(0.160)	(0.123)	(0.0870)	(0.0713)	(0.0772)	
3rd grade	-0.172	-0.317***	-0.082	-0.107		
	(0.158)	(0.115)	(0.0814)	(0.0846)		
4th grade	-0.089	-0.140	-0.124			
	(0.154)	(0.0972)	(0.0850)			
5th grade	-0.079	0.019				
	(0.125)	(0.0891)				
6th grade	-0.049					
	(0.113)					
Controls	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The figure reports estimates from regressions of the leave-one-out proportion of high-achiever peers in each grade. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Table 7: Cumulative Effects of High Achievers on Executive Function

	Lags			
	0	1	2	3
	(1)	(2)	(3)	(4)
1st grade	-0.270*	-0.565***	-0.167	-0.513***
	(0.160)	(0.176)	(0.154)	(0.152)
2nd grade	-0.249*	-0.170	-0.289**	
	(0.146)	(0.173)	(0.121)	
3rd grade	0.160	-0.529***		
	(0.168)	(0.165)		
4th grade	-0.419**			
	(0.168)			
Controls	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes

Notes: The figure reports estimates from regressions of the leave-one-out proportion of high-achiever peers in each grade on executive function test scores. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Table 8: Effects of High Achievers and Classroom Rank on Math Scores

	Full Sample		Top Performing (Q5)	
	(1)	(2)	(3)	(4)
Prop. of High Achiever Peers	-0.071	-0.070	-0.409***	-0.419***
	(0.066)	(0.066)	(0.110)	(0.108)
Students' Classroom Ranking	0.241***		0.094	
	(0.028)		(0.075)	
Mean of Dependent Variable	0.0193	0.0192	1.133	1.134
Observations	87303	87251	17880	17832
Controls	Yes	Yes	Yes	Yes
School-by-grade FE	Yes	Yes	Yes	Yes
Classroom Rank FE	No	Yes	No	Yes

Notes: The table reports estimates from regressions of the leave-one-out proportion of high-achiever peers and the classroom rank on math test scores. For Columns 1 and 3, classroom rank is define as a measure in percentiles (so rank is normalized to be between zero and one) similarly to Carneiro et al. (2025). For Columns 2 and 4, we include individual fixed effects for each percentile of the classroom rank. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

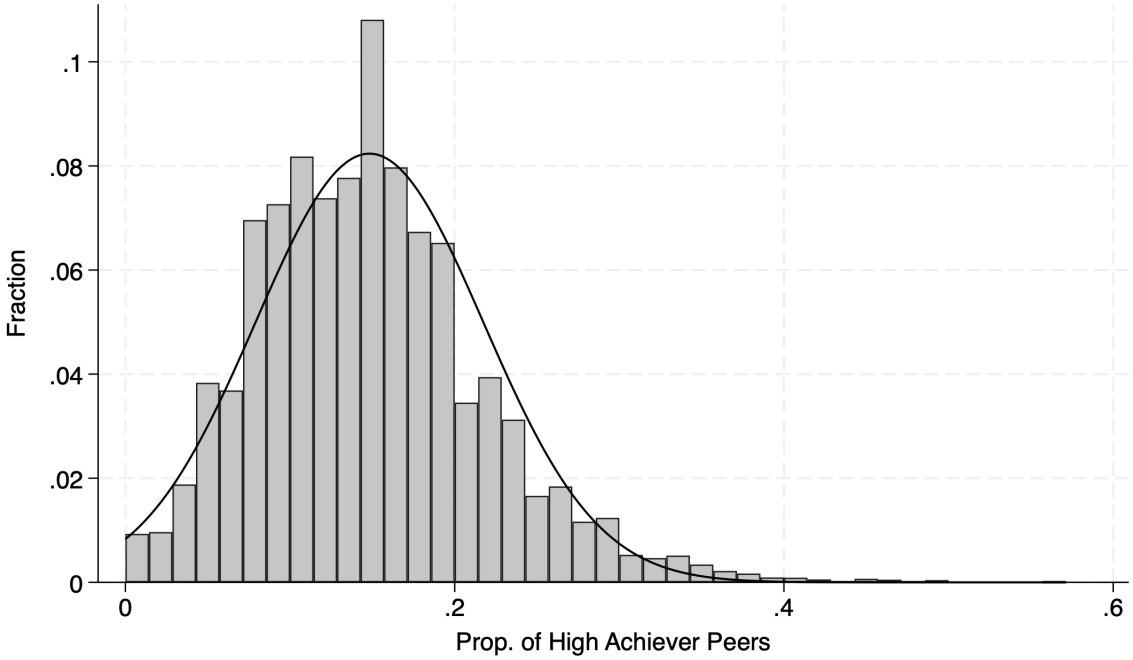
The Asymmetric Effects of High Achiever Peers: Experimental Evidence from Ecuador

Nicolás Fuertes-Segura Yyannú Cruz-Aguayo Carolina Echeverri

Online Appendix

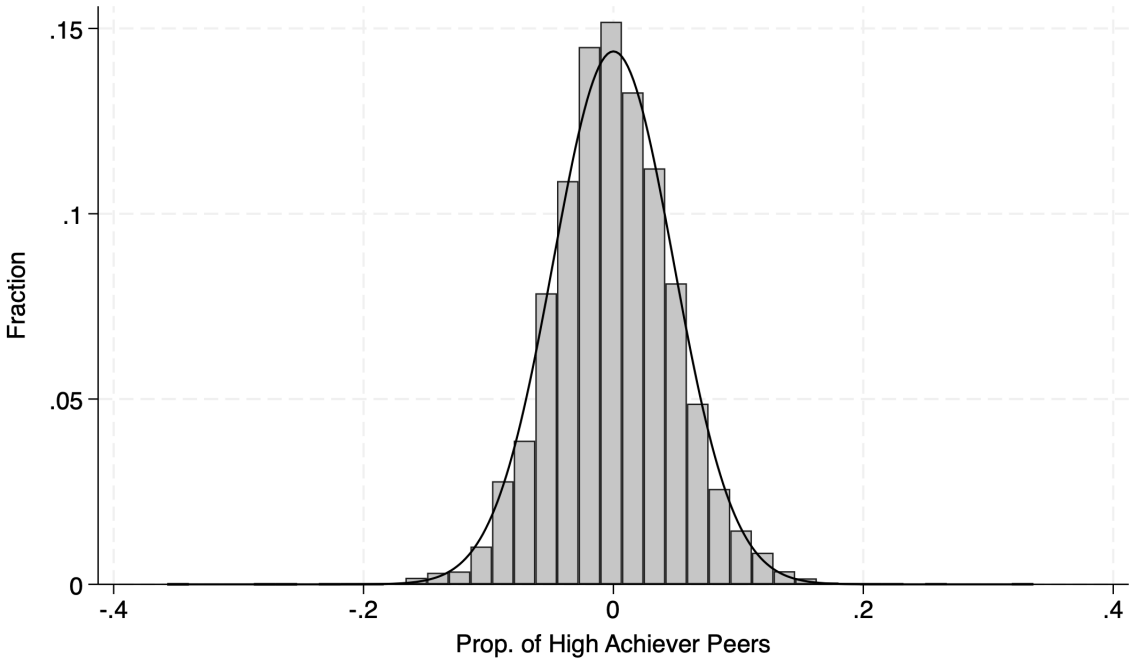
A Supplemental Figures and Tables

Figure A.1: Distribution of the Proportion of High Achievers Peers



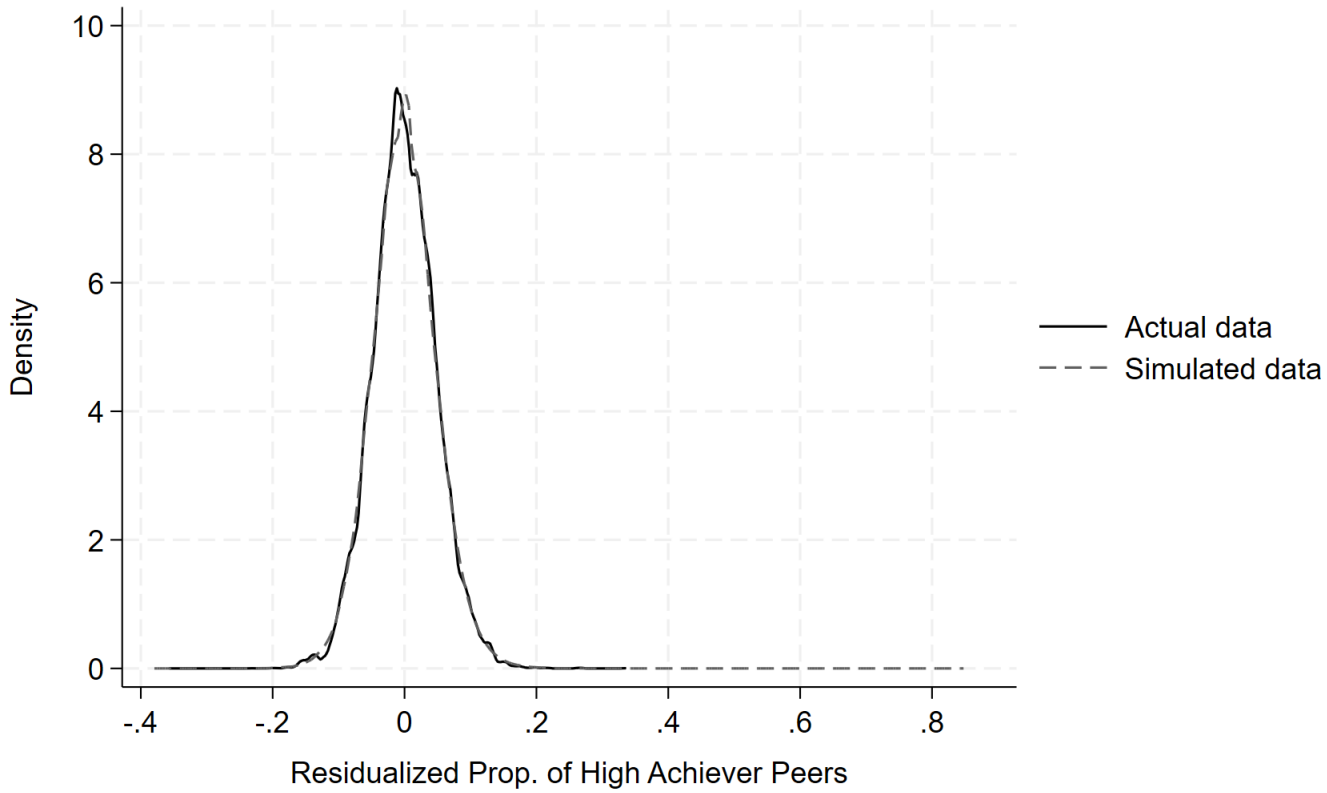
Notes: The figure above high achiever peer share distribution across school-grades. The overlaid curve represents the normal distribution.

Figure A.2: Residual Share of High Achievers Peers Across School-Grades



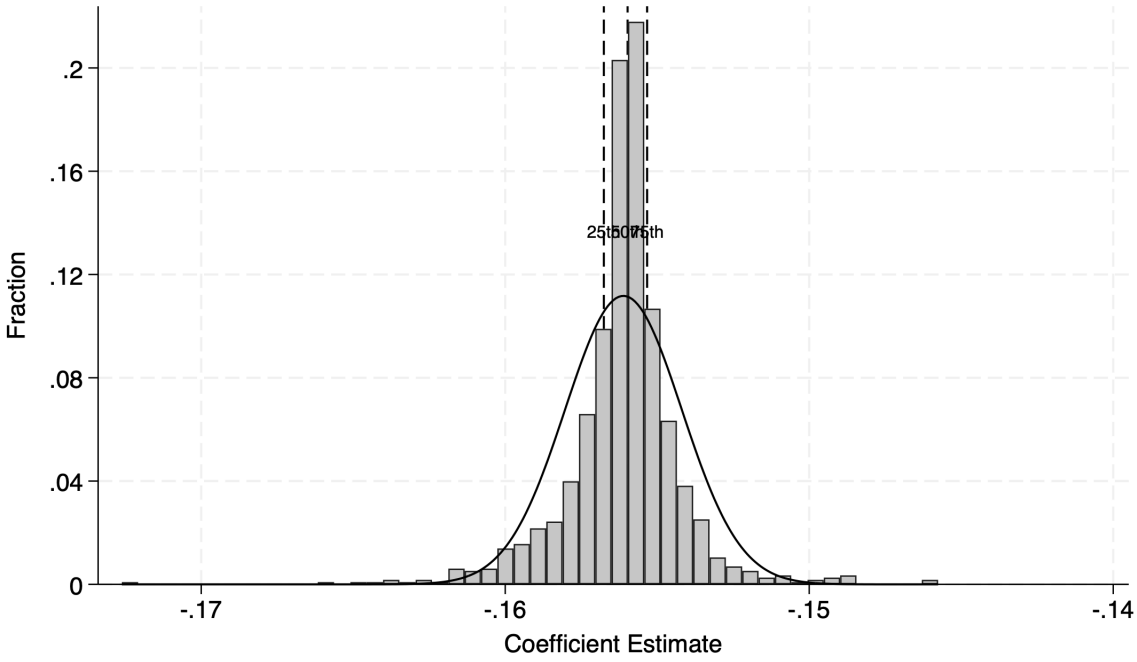
Notes: The figure above represents the residualized high achiever peer share distribution across school-grades, conditional on school-by-grade fixed effects. All regressions are limited to schools with at least two classrooms per grade. The overlaid curve represents the normal distribution.

Figure A.3: Simulated and Actual Residual Share of High Achievers Peers Across School-Grades



Notes: The figure above represents the residualized high achiever peer share distribution across school-grades, conditional on school-by-grade fixed effects. All regressions are limited to schools with at least two classrooms per grade. The overlaid curve represents the normal distribution.

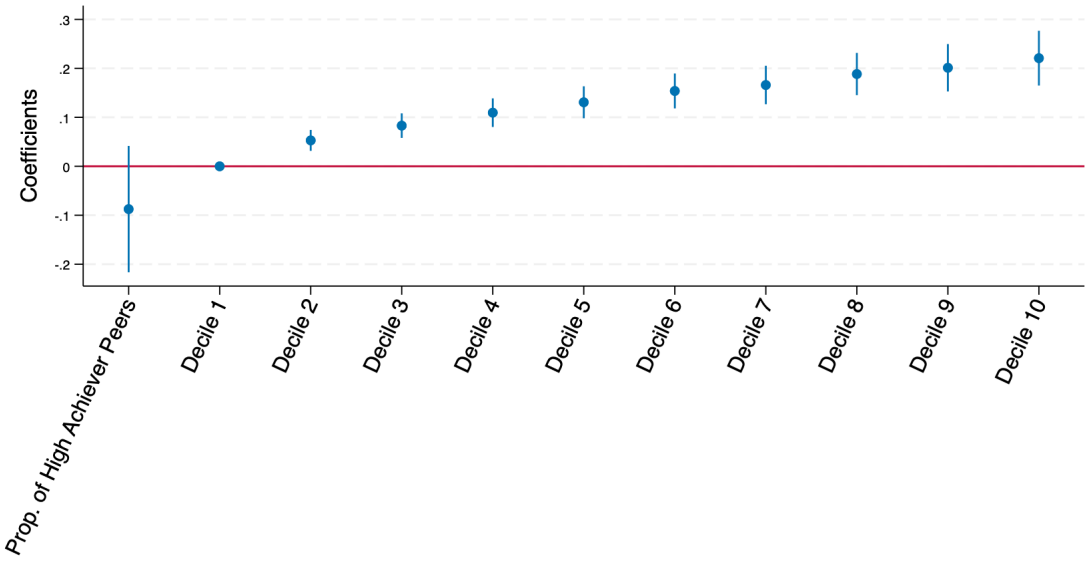
Figure A.4: Distribution of Coefficients of the Effect of High Achievers on Math Scores



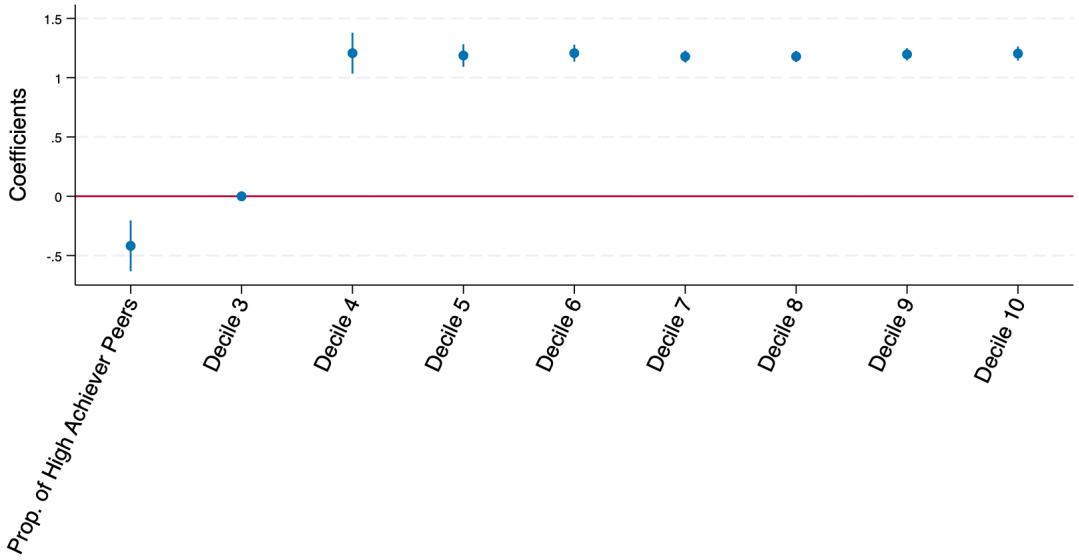
Notes: The figure above represents the distribution of the coefficients of leave-one-out regressions using the main specification. Each line represents the main specification with one school-grade committed from the sample. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. The overlaid curve represents the normal distribution.

Figure A.5: Effects of High Achievers and Classroom Rank Deciles on Math Scores

(a) Full Sample



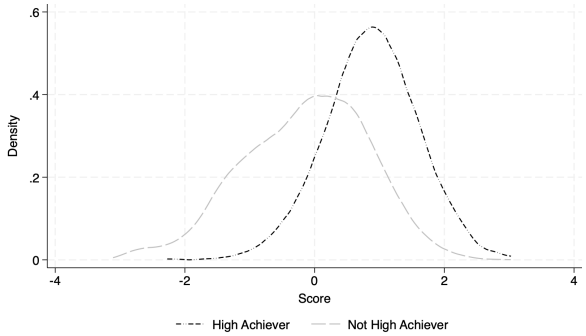
(b) Top Performing (Q5)



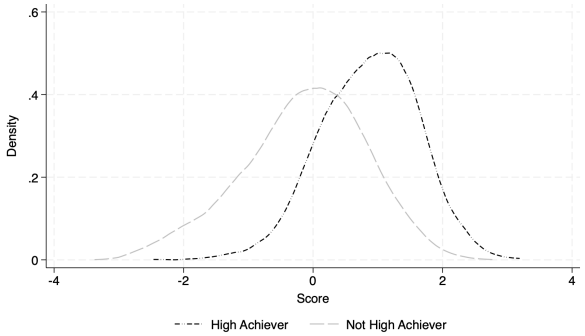
Notes: The figure reports estimates from regressions of the leave-one-out proportion of high-achiever peers and the deciles of classroom rank measure in percentiles (so rank is normalized to be between zero and one) similarly to Carneiro et al. (2025). All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Figure A.6: Distribution of Math Scores of high-achieving students

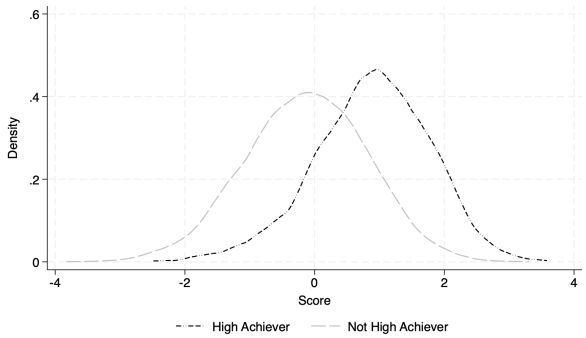
(a) 1st grade



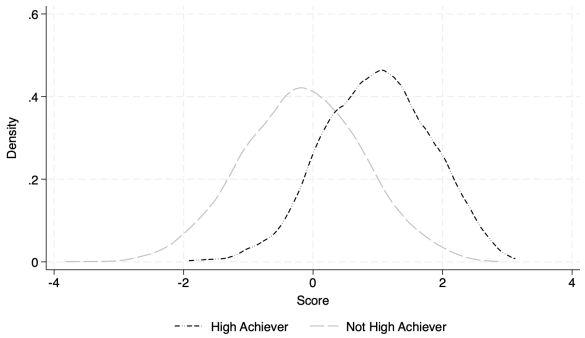
(b) 2nd grade



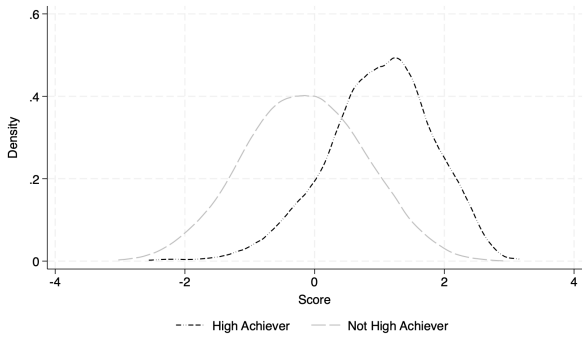
(c) 3rd grade



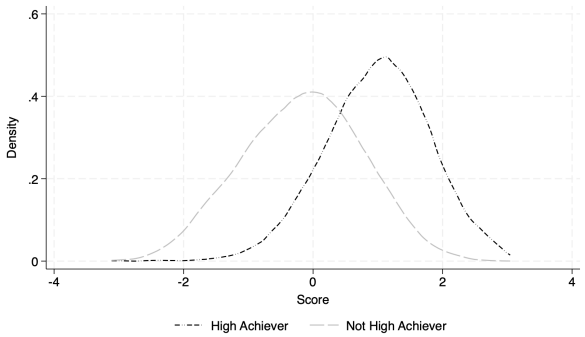
(d) 4th grade



(e) 5th grade



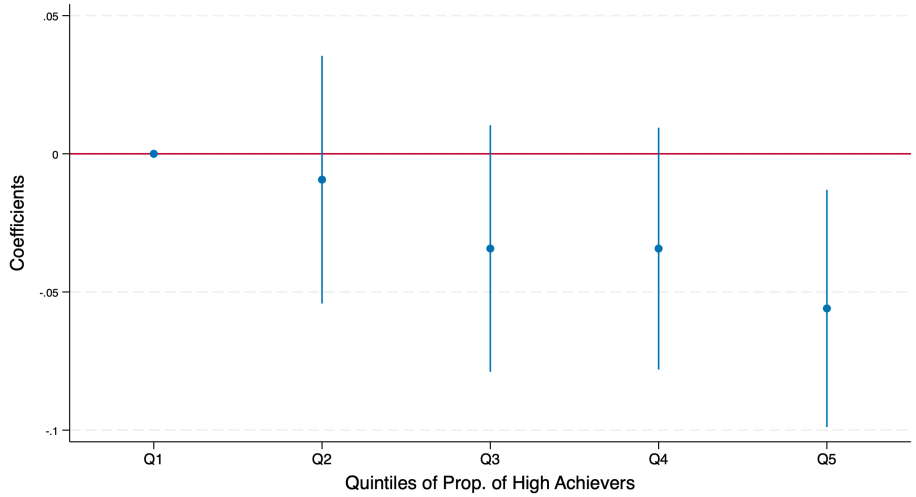
(f) 6th grade



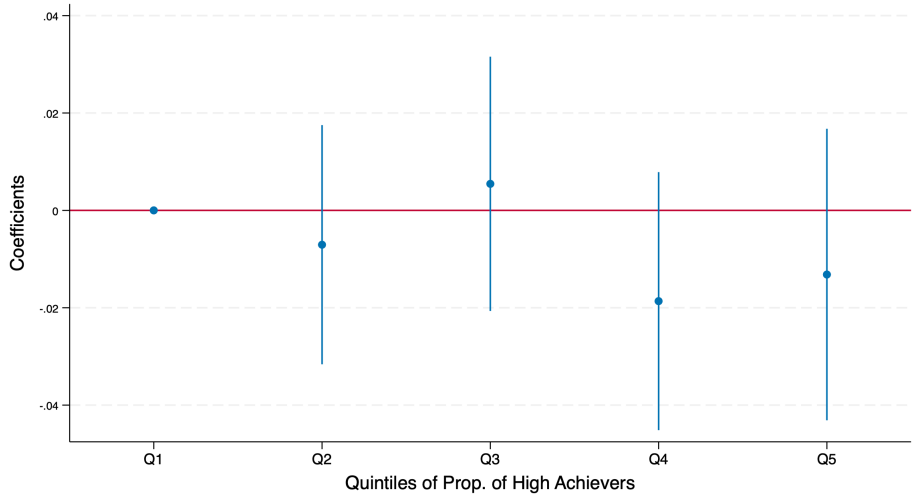
Notes: The figure above presents the univariate densities of the distribution of the math test score, separately for high achievers and non-high achievers based on teacher rankings, by grade.

Figure A.7: Interaction of Non-Linear Effects and School Size

(a) Small Schools



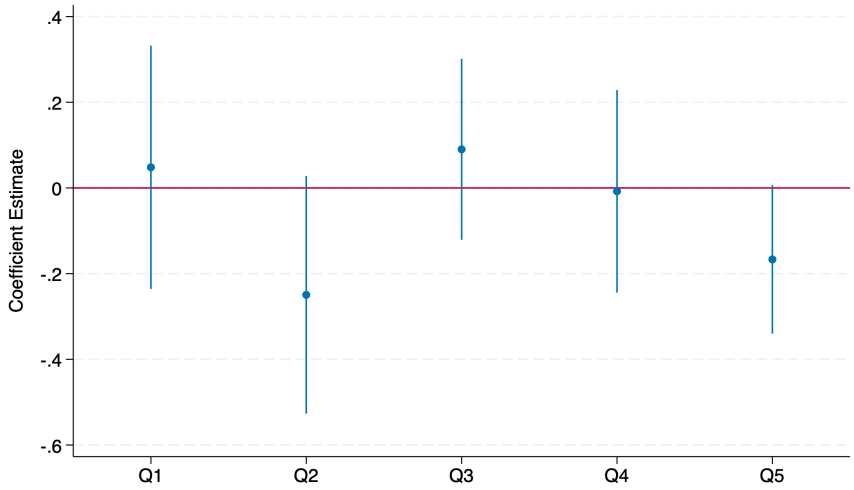
(b) Big Schools



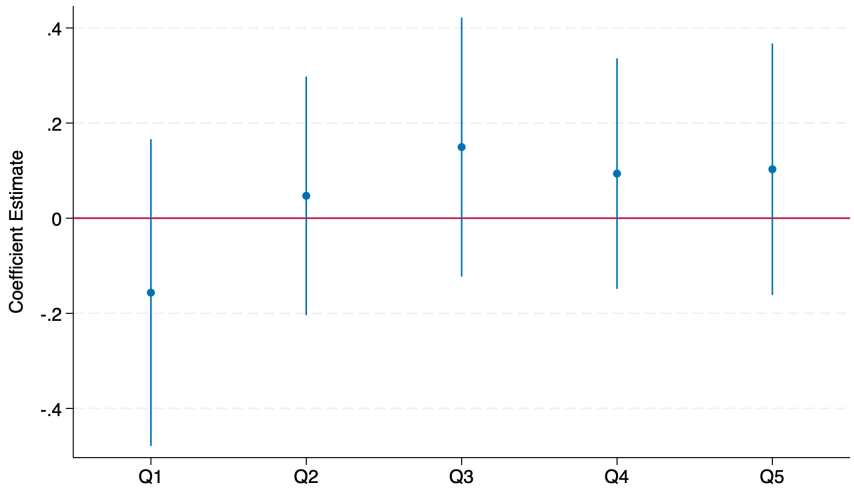
Notes: The figure above represent the distribution of the coefficients of separate regressions using the main specification on each school-by-grade. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. The overlaid curve represents the normal distribution.

Figure A.8: Heterogeneous Effects of High Achievers on Happiness and Effort by Previous Math Test Results

(a) Happiness



(b) Effort



Notes: The figures above report estimates from regressions of the leave-one-out proportion of high-achiever peers on happiness and effort by quintiles of the math test result in the previous year. All regressions are limited to schools with at least two classrooms per grade. Vertical bars represent 95% confidence intervals. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Table A.1: Characteristics of Female and Male high-achieving students

	Male	Female	Difference (1)-(2)
	(1)	(2)	(3)
A. Children characteristics			
Age of child (in months) in 2012	61.429	60.938	0.492**
	(5.031)	(4.595)	(0.222)
Receptive vocabulary score (PPVT)	92.209	91.137	1.071
	(16.673)	(16.703)	(0.768)
Proportion who attended preschool	0.640	0.650	-0.010
	(0.480)	(0.477)	(0.022)
B. Household Characteristics			
Mother's years of completed schooling	9.822	9.837	-0.015
	(3.978)	(3.910)	(0.184)
Father's years of completed schooling	9.480	9.465	0.015
	(4.065)	(3.968)	(0.208)
Mother's age	30.798	30.638	0.160
	(6.861)	(6.360)	(0.310)
Father's age	35.368	34.314	1.054**
	(8.420)	(7.358)	(0.412)
Household has piped water in home	0.859	0.826	0.033**
	(0.348)	(0.380)	(0.017)
Household has flush toilet in home	0.457	0.484	-0.027
	(0.498)	(0.500)	(0.023)

Notes: Table reports summary statistics of the children in the sample. It includes children's characteristics and those of their household.

Table A.2: Variation in Proportion of High Achievers After Removing Fixed Effects

	Mean	SD	Median	Min	Max
A. Raw variables					
Proportion of High Achievers	0.15	0.07	0.14	0.00	0.57
B. Residuals after removing school-by-grade FE					
Residuals of Proportion of High Achievers	-0.00	0.05	-0.00	-0.36	0.35

Notes: The table above reports the raw variation in the leave-one-out proportion of high achievers and the variation that is left after removing school-by-grade fixed effects. The table only includes schools with at least two classrooms per grade.

Table A.3: Effects on Cognitive Test Scores Components

	Math			Executive Function		
	Number recognition and arithmetic	Number sense	Word problems	Cognitive Flexibility	Working Memory	Inhibitory Control
	(1)	(2)	(3)	(4)	(5)	(6)
Prop. of High Achiever Peers	-0.165*	-0.255***	-0.254***	-0.235***	-0.182**	-0.186
	(0.095)	(0.074)	(0.068)	(0.087)	(0.083)	(0.123)
Mean of Dependent Variable	0.017	0.020	0.013	0.011	0.016	0.012
Treatment Effect of 1SD increase	-0.011	-0.018	-0.018	-0.017	-0.013	-0.011
Observations	87225	87093	87303	56626	56626	29984
Controls	Yes	Yes	Yes	Yes	Yes	Yes
School-by-grade FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates from regressions of the leave-one-out proportion of peers based on their parents' education. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

B Randomization details

Table B.1: Testing for random assignment of children to classrooms, math

	Kindergarten	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
Test statistic	1.359	-0.383	0.905	0.300	-0.445	-0.222	0.980
P-value	0.174	0.702	0.366	0.764	0.657	0.825	0.327

Notes: The table reports results for tests of random assignment of children to classrooms within schools using a methodology proposed by Jochmans (2023). The null hypothesis is the absence of correlation between a child's ability measured at the end of the previous grade and the average ability of classroom peers assigned to her at the beginning of a given grade, conditional on school. The sample includes all children.

C Details on the Tests and IRT

In this appendix, we cover more details on tests applied and the IRT procedure implemented to calculate the math test scores. First, Table C.1 and Table C.2 show summary statistics of each of the tests applied by grade for math and executive function, respectively.

We normalize the end-of-year tests by subtracting the mean and dividing by the national sample's standard deviation. We then create three test aggregates for math and executive function, respectively. Each of the four tests within an aggregate receives the same weight. Like the underlying tests, the aggregates are normalized to have zero mean and unit standard deviation.

Table C.1: Summary Statistics for Math Test Score Components

	N	Mean	SD
A. Kindergarten			
Number identification	14522	0.372	0.229
Block rotation	14522	0.805	0.156
Sequences	14522	0.256	0.299
Word problems	14512	0.252	0.163
B. 1st Grade			
Number identification	16158	0.653	0.175
Arithmetic	17265	0.362	0.246
Word problems	16353	0.491	0.254
Number line	16368	0.782	0.123
C. 2nd Grade			
Sequences	18481	0.399	0.234
Position Value	16846	0.366	0.136
Arithmetic	18481	0.406	0.230
Word problems	18393	0.300	0.190
Number line	16874	0.841	0.073
D. 3rd Grade			
Sequences	17521	0.496	0.231
Word problems	17521	0.390	0.208
Position Value	17521	0.386	0.182
Arithmetic	17521	0.527	0.227
Number line	17277	0.847	0.095
E. 4th Grade			
Sequences	17432	0.091	0.074
Word problems	17424	0.078	0.101
Position Value	17424	0.058	0.067
Arithmetic	17426	0.205	0.150
F. 5th Grade			
Sequences	17529	0.538	0.219
Word problems	17529	0.481	0.208
Position Value	17529	0.453	0.201
Arithmetic	17529	0.455	0.220
G. 6th Grade			
Sequences	17266	0.483	0.240
Word problems	17266	0.411	0.178
Position Value	17266	0.564	0.251
Arithmetic	17266	0.466	0.209

Notes: The table presents the results from pairwise correlations between CLASS score and its components collected from Kindergarten to 4th grade. All the correlations are significant at the 1 percent level.

Table C.2: Summary Statistics for Executive Function Score Components

	N	Mean	SD
A. Kindergarten			
Memory	14522	0.269	0.208
Card sorting	14511	0.799	0.225
Day and night	14506	0.848	0.242
Indicators comprehension	14519	0.617	0.166
B. 1st Grade			
Memory	17227	0.310	0.186
Card sorting	17227	0.857	0.247
Pair Cancellation	16347	0.240	0.095
Matrix	17227	0.485	0.294
C. 2nd Grade			
Memory	16839	0.445	0.197
Card sorting	18393	0.696	0.232
Pair Cancellation	16848	0.370	0.114
Words and colors - Stroop	14354	0.218	0.071
Numbers and amounts - Stroop	18393	0.833	0.270
D. 3rd Grade			
Triangles and squares	17518	0.695	0.163
Memory	17518	0.425	0.202
Pair Cancellation	17279	0.428	0.109
Words and colors - Stroop	16142	0.240	0.061
E. 4th Grade			
Triangles and squares	17424	0.768	0.146
Memory	17425	0.466	0.161
Pair Cancellation	17434	0.454	0.112
Words and colors - Stroop	16920	0.271	0.066

Notes: The table presents the results from pairwise correlations between CLASS score and its components collected from Kindergarten to 4th grade. All the correlations are significant at the 1 percent level.

D Application of the CLASS in Ecuador

CLASS Protocol

In this appendix, we cover minute details of the Classroom Assessment Scoring System (CLASS) (Pianta et al., 2015) application protocol and how it was applied in Ecuador. We use the CLASS to measure teacher behaviors. The CLASS measures teacher behaviors in three domains: Emotional Support, Classroom Organization, and Instructional Support. Emotional support includes children's emotional and social expressions in the classroom, Classroom Organization relates to the classroom routines and teachers' proactiveness, and Instructional Support is related to promoting order thinking and providing quality feedback.

Each of the domains is composed of three of four dimensions that are scored separately by the coders. Figure D.1 provides an overview of the dimensions included in each domain. For each dimension, the CLASS protocol gives coders concrete guidance on whether the score given should be "low" (scores of 1–2), "medium" (scores of 3–5), or "high" (scores of 6–7). Each domain is scored individually, and the coders look for specific behaviors. For example, within the behavior management dimension, a coder would assess whether there are clear behavior rules and expectations and whether these are applied consistently. The CLASS protocol would assign a high score to a teacher whose rules and expectations for behavior are clear and consistently enforced. In contrast, a teacher whose rules and expectations are absent, unclear, or inconsistently enforced would be assigned a low score. (See Appendix Table B1 in Araujo et al. (2016) for more details). Under the CLASS protocol, the scoring process does not consist of running down a checklist of the presence or absence of certain behaviors or indicators but a holistic and composite description of the classroom experience.

Application in Ecuador

We filmed all teachers for an entire school day (from approximately eight to one in the afternoon for morning schools and from two to six in the afternoon for the afternoon schools).

Teachers only knew on what day they would be filmed until the day itself. Following CLASS protocols, we discarded the first hour of filming, times that were not instructional (e.g., lunch and breaks), and where the main teacher was not in the classroom (e.g., PE Class). The remaining video was cut into usable 20-minute segments in which at least five children and their main teacher were in the segment for at least 15 of the 20 minutes that the segment ran. For each teacher, we selected the first four segments that comply with the protocol (over 9,000 segments in total).

Once the videos were separated into segments, a group of 6-8 coders explicitly trained for this purpose by a Teachstone-certified CLASS K-3 trainer scored them. The trainer also provided feedback and supervised the coders while coding the segments. All the segments were double-coded by two independent coders who scored each segment on the ten dimensions explained previously. The videos with large differences in their scores between the two coders were flagged and sent to a third coding process by an independent coder.[27] Additionally, during the entire process, we interacted extensively with the developers of the CLASS at the University of Virginia.

Figure D.2 graphs univariate densities of the distribution of CLASS score and each domain by grade. The figure shows that teachers score the highest in Classroom Organization, with teachers distributed in the "medium" and "high" parts of the distribution; somewhat lower in Emotional Support, with most teachers in the "medium" range; and lowest in Instructional Support, where all teachers have "low" CLASS scores. As a result, most teachers have a medium total Score in the CLASS, and some are in the Low score range.

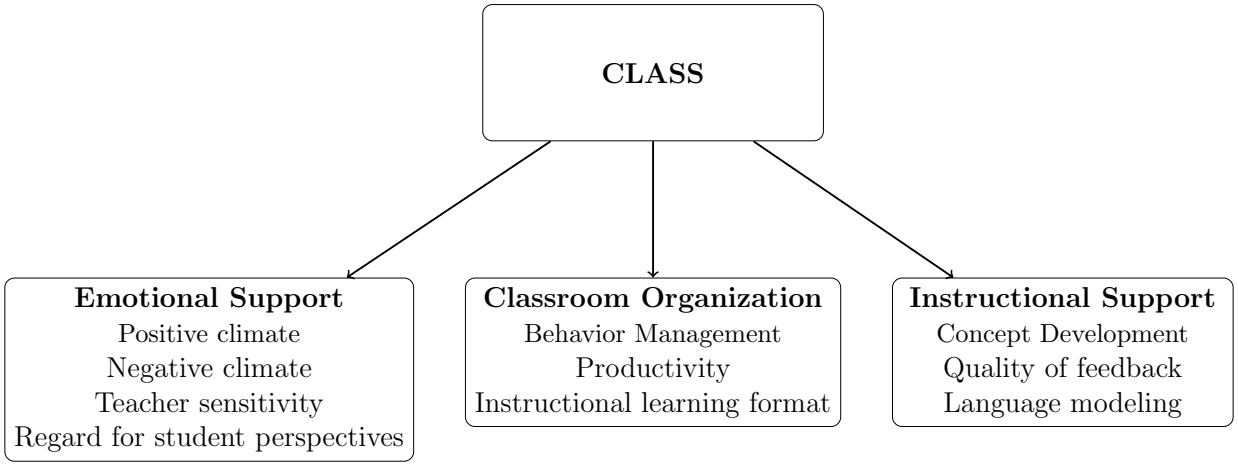
Table D.1 shows the correlation between the total CLASS score and each of its components. It shows that the components' scores are highly correlated with the total, which is consistent with how the total score is calculated. Moreover, it shows that the correlation among components is lower, consistent with the fact that each measures different behaviors

[27]Based on a preliminary analysis of CLASS data from Ecuador that revealed a breakdown of high-and low-variability dimensions, videos are coded a third time if they have a difference of more than 1 point in the dimensions of Negative Climate, Concept Development, Quality of Feedback, or Language Modeling; if there is a difference of more than 2 points in any of the other dimensions they are also flagged for re-coding

and dimensions of the teacher's quality.

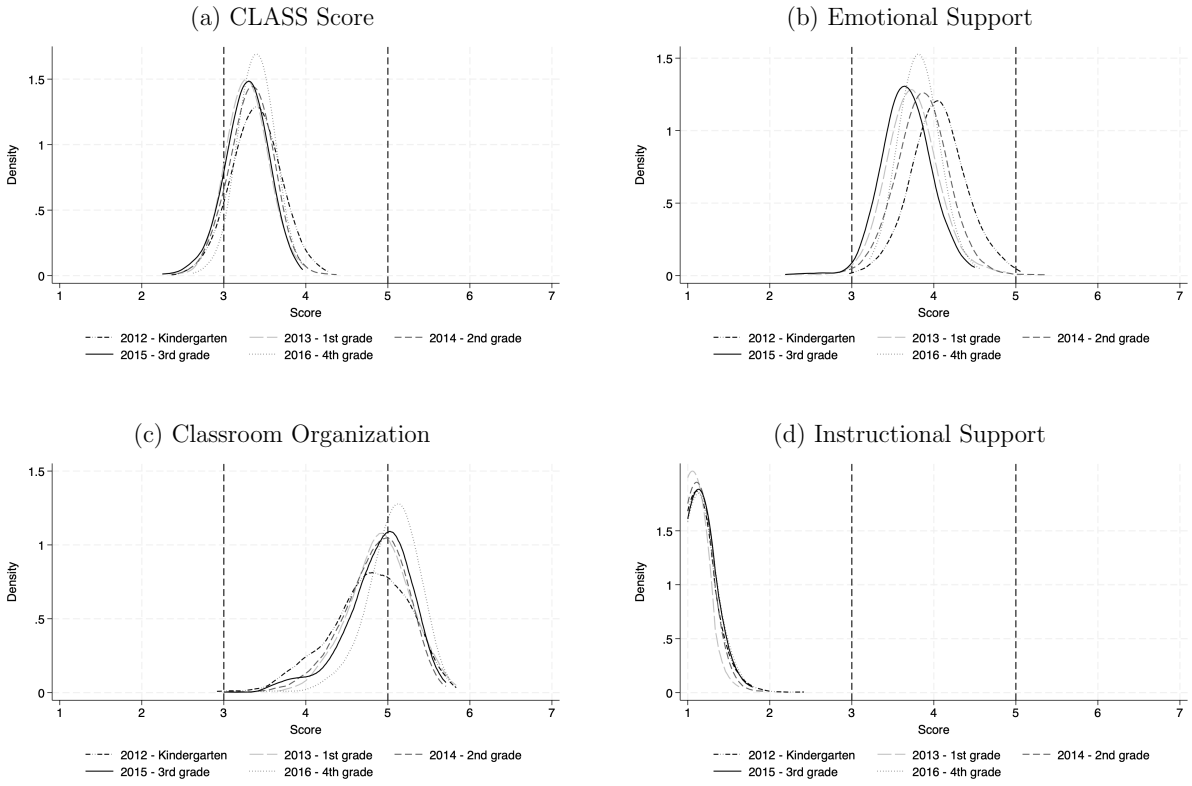
The filming and coding Protocols for the CLASS in Ecuador provide further details on how the process was implemented and how the segments were scored. The authors provide these upon request.

Figure D.1: ClASS Domains and Dimensions



Notes: The figure shows the three domains of the Classroom Assessment Scoring System (CLASS) and the dimensions included in each domain.

Figure D.2: Distribution of CLASS Score and domains



Notes: The figure above presents univariate densities of the distribution of Classroom Assessment Scoring System (CLASS) score and its domains, by grade.

Table D.1: Correlation across CLASS scores

	Total Score	Emotional Support	Classroom Organization	Instructional Support
	(1)			
	CLASS_	CLASS1_	CLASS2_	CLASS3_
Total Score	1.000			
Emotional Support	0.881	1.000		
Classroom Organization	0.862	0.563	1.000	
Instructional Support	0.587	0.391	0.398	1.000

Notes: The table presents the results from pairwise correlations between CLASS score and its components collected from Kindergarten to 4th grade. All the correlations are significant at the 1 percent level.

E Extra Robustness Checks

Peer's Parents Education

In this appendix, we estimate the main results in Table 3 using the peer's parents education which has been used in the US context to estimate the effect of high flyers (see Cools et al. (2022)). In particular, these studies use the proportion of leave-one-out proportion of peers with at least one post-college parent. In our context, we are not able to separate college and post-college. For that reason, in Table E.1, we present the results using the leave-one-out proportion of peers with at least one post-secondary parent. The table shows that the coefficients are negative but not significant.

Nevertheless, whether using the proportion of peers with at least one post-secondary parent is appropriate in the context of Ecuador is unclear, given that the proportion of children who have at least one post-secondary parent is smaller. Table E.2 shows that the proportion of children that have at least one post-secondary school is 13.01%. While in the US around 25% of the children have at least one post-college parent (Cools et al., 2022). Given this, in order to define a similar proportion of children as high flyers in both countries, it is necessary to adjust the parents education conditions in Ecuador. Table E.2 shows that around 22% of the children in Ecuador have parents who have finished secondary school.

Table E.3 shows that the results using the proportion of children that both parents finished secondary school are mostly consistent with the results in Table 3 for Executive function. In particular, Executive function skill test scores reduce by 0.014 SD when the proportion increases by one standard deviation. Although math scores do not exhibit significant decreases, this is potentially due to the loss of identifying variation from the smaller sample size. However, it is important to note that the coefficient sign remains the same on all of the estimates.

Table E.1: Effects of Peers' Parents Post-Secondary Education on Cognitive Skills

	Math	Executive Function
	(1)	(2)
Prop. of Peers with at least one Post-Secondary Parent	-0.044	-0.106
	(0.058)	(0.081)
Mean of Dependent Variable	0.054	0.038
Treatment Effect of 1SD increase	-0.005	-0.011
Observations	72298	54629
Controls	Yes	Yes
School-by-grade FE	Yes	Yes

Notes: The table reports estimates from regressions of the leave-one-out proportion of peers that have at least one parent with post-secondary education. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Table E.2: Proportion of children by parents' education

	Percentage of Children
At least one post-secondary parent	13.01%
Both parents finished secondary school	21.55%

Notes: The table reports the proportion of children whose parents have certain education characteristics in Ecuador.

Table E.3: Effects of Peers' Parents Secondary Education on Cognitive Skills

	Math	Executive Function
	(1)	(2)
Prop. of Peers with Parents who finished Secondary	-0.048	-0.111*
	(0.052)	(0.059)
Mean of Dependent Variable	0.054	0.038
Treatment Effect of 1SD increase	-0.007	-0.016
Observations	72298	54629
Controls	Yes	Yes
School-by-grade FE	Yes	Yes

Notes: The table reports estimates from regressions of the leave-one-out proportion of peers that have at least one parent with post-secondary education. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Attrition

In this appendix, we estimate if having a higher proportion of high achievers increases the probability that a child attrits from our sample of school in between grades. Appendix Table E.4 shows the impact of the (leave-one-out) proportion of high achievers on the likelihood of leaving the sample between two consecutive grades. It shows that the children are no more likely to attrit when exposed to a higher proportion of high achievers. Therefore, we do not see evidence of selective attrition. Nevertheless, in Appendix Table E.5, we restrict our sample to the balanced panel of children and estimate the main equation. We find that the results are similar.

Table E.4: Effects of High Achievers on Attrittion

	All grades	2nd grade	3rd grade	4th grade	5th grade	6th grade
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Prop. of High Achiever Peers	-0.004	-0.001	0.002	-0.037	0.019	-0.000
	(0.011)	(0.031)	(0.013)	(0.041)	(0.017)	(0.015)
Mean of Dependent Variable	0.0187	0.0392	0.00745	0.0338	0.00873	0.00745
Observations	68481	11794	13287	14329	14312	14759
Controls	Yes	Yes	Yes	Yes	Yes	Yes
School-by-grade FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates from regressions of the lagged leave-one-out proportion of high achievers on the likelihood of being an attritor between t and $t+1$. The first column pools all the grades in a single regression and the remaining columns correspond to a different grade. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.

Table E.5: Effects of High Achievers on Cognitive Skills

	Math	Executive Function
	(1)	(2)
Prop. of High Achiever Peers	-0.161**	-0.299***
	(0.080)	(0.100)
Mean of Dependent Variable	0.086	0.063
Treatment Effect of 1SD increase	-0.011	-0.021
Observations	51168	38492
Controls	Yes	Yes
School-by-grade FE	Yes	Yes

Notes: The table reports estimates from regressions of the leave-one-out proportion of high-achiever peers on cognitive skills. All regressions are limited to schools with at least two classrooms per grade. All models include controls for children's biological sex, age, age squared, and the lagged test score in the previous year or baseline. *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. Standard errors are corrected for heteroskedasticity and are clustered at the school level.