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Experimental Evidence from Mexico

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Abstract

This study examines the gendered effects of early and sustained exposure to high-performing peers on female educational trajectories. Exploiting random allocation to classrooms within middle schools, we measure the effect of male and female high performers on girls' high school placement outcomes. We disentangle two channels through which peers of either sex can play a role: academic performance and school preferences. We also focus on the effects of peers along the distribution of baseline academic performance. Exposure to good peers of either sex reduces the degree to which high-achieving girls seek placement in more-selective schools. High-achieving boys have particularly strong, negative effects on high-performing girls' admission scores and preferences for more-selective schools. By contrast, high-achieving girls improve low-performing girls' placement outcomes, but exclusively through a positive effect on exam scores.

Keywords: Peer effects, Gender, High achievers, Secondary education, Mexico.
JEL classifications: C93, I21, I24, J16, J24.

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1 Introduction

An overwhelming number of studies on the economics of education shows that peer composition can greatly impact students' outcomes through a number of channels including direct peer-to-peer support and externalities in the classroom [Hoxby, 2000], concerns about comparative academic ranking [Tincani, 2017; Weinhardt and Murphy, 2020], propensity to engage in risky behavior [Card and Giuliano, 2011; Lavy et al., 2011], and educational and career choices [De Giorgi and Pellizzari, 2014; Carrell et al., 2018; Bifulco et al., 2014]. In the last couple of decades, the literature on peers effects has advanced through a stronger emphasis on natural experiments and randomization, in a search to identify credible sources of exogenous variation in peer composition that overcome selection issues [Sacerdote, 2014]. Some studies have exploited random allocation of students to groups or roommates [Carrell et al., 2013; Frijters et al., 2019; Stinebrickner and Stinebrickner, 2006], while a few experimental studies have attempted to measure the effects of specific classroom formation strategies [Duflo et al., 2011; Booij et al., 2017; Carrell et al., 2013].

The progress made in the study of peer effects in educational settings shows that the measured size and nature of peer effects is quite mixed, with important variations across contexts. The evidence also points out that the linear-in-means model fails to capture peers' interactions and that instead the effects of peers on individual behavior and performance tend to be highly heterogeneous depending on individual characteristics. A rich and growing line of research provides evidence that women and men are likely to differ in terms of socio-emotional traits.[1] This could have important implications for the way their behavior is influenced by peers. Therefore, a recent strand of the peer effects literature has focused on the asymmetric gendered effects of peers. This paper studies the potentially gendered impacts of early and sustained exposure to good peers during middle school in Mexico. We measure the effect of this exposure on girls' high school placement outcomes, and disentangle the role of academic performance and school preferences as potential channels.

Our research design relies on a sample of 50 middle schools in Mexico City and exploits random variation in classroom allocation within each school to study how exposure to high-performing boys and girls affect girls' individual educational outcomes. We define the share of high-achieving girls and boys as the main variables of interest. To avoid reflection problems, we determine high performers based on the scores obtained on the exam taken to gain admission to middle school. This exam is taken during the last year of elementary school,

[1]For instance, Alan and Ertac [2018] find that women tend to be less competitive while Buser et al. [2014] identify lower overconfidence levels among females when compared to their male counterparts. In educational settings, Rask and Tiefenthaler [2008] find that women are more sensitive to grades while Bordalo et al. [2019] shows that women tend to be less confident than men in math-related subjects.

before applicants actually meet their middle school peers. To get placed, the public school system in Mexico City runs a centralized allocation process that seats about 150,000 students in 780 public middle schools. Using a Boston allocation mechanism, applicants are placed based on their submitted ranked preferences and their priority index, as defined by individual exam scores. We embed the random allocation of students to classrooms within this context, which generates large variation in the share of high achievers across classes, within the same school. We conduct several checks to verify that the randomization of students yields shares of high-performing boys and girls in the classroom that are not correlated with pre-treatment individual characteristics.

We rely on administrative records on the high school admission process in Mexico City to measure the impact of the shares of female and male high performers on placement outcomes and explore the underlying channels. To request admission to a public high school, students go through another centralized allocation mechanism that admits close to 240,000 students to about 630 schools in the metropolitan area of Mexico City. Graduating middle school students apply at the end of ninth grade by submitting a registration form and taking another placement exam. Placement to high school relies on a deferred acceptance mechanism that also depends on students' rank order lists and their performance in the admission test. We measure the impact of middle school peers on high school placement outcomes and disentangle between the effects on exam performance and aspirations, the latter measured by students' revealed preferences for schools.

Our results show that exposure to good peers of either sex negatively impacts high-achieving girls' placement outcomes in terms of school selectivity. High-achieving boys' have particularly strong negative effects on high-performing girls' admission scores and preferences for selective schools. Performance records during middle school show that the negative effect of exposure to high-ability boys in the classroom does not materialize right away, but instead starts to become visible in the second year of middle school. In turn, female high achievers improve low-performing girls' placement outcomes through a positive effect on exam scores. This "protective effect" is absent when looking at the effect of high-achieving boys on low-performing girls in the classroom.

Our results contribute to the understanding of gender gaps in early educational trajectories, which can have long-term effects in the labor market. We focus on the role of a key environmental factor at a crucial developmental stage, adolescence, when peers' influence can be very compelling. Moreover, the richness of the administrative records allows us to shed light on the strength of underlying academic aspects, *vis-a-vis* aspirational channels in the effect that high-achieving boys and girls have on girls' decisions to seek (and potentially gain) a seat in selective schools.

The study of asymmetric gendered effects of peers on educational and labor trajectories has mostly focused on the role of the share of female students in the classroom. For example, studies show that a higher proportion of female students improves performance among both sexes –in elementary school [Hoxby, 2000] and, indeed, throughout elementary, middle and high school [Lavy and Schlosser, 2011]. Focusing on the tertiary education level, Zölitz and Feld [2020] show that a higher proportion of female peers decreases (increases) the probability of choosing a male-dominated major among women (men) in college. In turn, Fischer [2017] finds that the presence of higher-ability peers reduces the likelihood that women graduate from university with a major in science, technology, engineering and mathematics (STEM), but does not affect the persistence of STEM majors among men.

A more recent strand of the literature focuses on both the gender of peers *and* their impact on individual outcomes by gender. Exploiting idiosyncratic cross-cohort, within-school variation in classroom composition in the United States, Cools et al. [2020] show that greater exposure to high-achieving males in middle and high school decreases the likelihood that females complete a bachelor's degree. Under the same quasi-random identification strategy in China, Mouganie and Wang [2020] find that exposure to a higher share of high-achieving girls during high school encourages females to choose a science track, while exposure to more high-performing males decreases this likelihood; overall, they fail to identify substantial peer effects among boys. Recent work by Zölitz and Feld [2018] exploits random allocation of students to sections in a Dutch business school. Their results show that having high-achieving male peers reduces (increases) the probability of choosing math majors for females (males); by contrast, high-achieving females have no impact on college choices of either sex. Balestra et al. [2021] focuses on the transition from primary to secondary school in the Swiss system and looks at the role of "gifted" peers on achievement in secondary school, enrollment in post-compulsory education, and occupational choices. They find that the impact of gifted students is highly heterogeneous, with male high achievers students benefiting the most from their presence. Female students only benefit from the presence of female gifted students. Their results show that exposure to gifted students in school has long-lasting consequences as they increase the likelihood of choosing a selective academic track as well as occupations in STEM fields.

Our paper focuses on the effects of high-ability peers on adolescent girls by building on these related studies. Our study is closely linked to Cools et al. [2020], Mouganie and Wang [2020], and Balestra et al. [2021] in terms of the focus on the share of high achievers (or gifted students in the latter) by sex, rather than the average ability of each group. Our identification strategy exploits classroom-level variation in the share of high achievers yielded by random allocation of students to classes as in Zölitz and Feld [2018].

This paper contributes to the literature in five ways. First, we expand the focus of this literature to a previously unexplored setting, Mexico, a large upper middle income economy in Latin America. This is particularly important, given that the size of peer effects greatly varies across different contexts.

Second, we overcome reverse causality issues by relying on standardized ability measures captured *before* students begin middle school. By contrast, Cools et al. [2020] use parental education as a proxy of performance before peers meet and interact in school, while Zölitz and Feld [2018] rely on college GPAs once all students in their sample are already attending the business school. Though Mouganie and Wang [2020] identify high-performing students based on individual performance in the national high school entrance exam, they focus exclusively on the math portion of the exam because they are only interested in STEM track choices. Balestra et al. [2021] rely on a measure of gifted students, status that is determined when the child is between six and nine years old. However, identification of a gifted child is plausibly endogenous and is prone to measurement errors, as a request to conduct specialists' assessment and IQ tests has to be made by the teachers (or parents).

Third, we are able to exploit random allocation of students to classes in a sample of 50 middle schools in Mexico City. We thus move beyond quasi-experimental strategies that rely on cross-cohort, within-school variation at the grade level [Mouganie and Wang, 2020; Cools et al., 2020]. We also expand the external validity of our analysis relative to Zölitz and Feld [2018], who do have random allocation of students to sections, but within one school.

Fourth, we are able to disentangle two main channels of the effects of high-performing peers on high school placement outcomes – distinguishing the effects that are due to changes in academic performance from those that can be attributed to changes in school preferences. Relative to self-reported (and very often hypothetical) survey questions on subjective beliefs and perceptions used in other studies, revealed preferences data provide a more reliable approach to measure girls' aspirations. We acknowledge that rank order lists do not help us disentangle between the different underlying factors behind girls' aspirations (e..g, norms at home or parental preferences). However, we posit that our approach is relevant as it allows us to measure aspirations based on *actual* choices instead of hypothetical survey answers. This novel contribution also allows us to delve deeper into the mechanisms behind gendered peer effects.

Fifth, we build on Cools et al. [2020], who also look at grades, and exploit the richness of our administrative records to explore the dynamic gendered peer effects on girls' achievement during middle school. We evaluate the evolution of performance between middle and high school using standardized exam scores – thus avoiding grading issues that emerge when comparing GPAs across schools. We also rely on survey data to measure the effect of good peers on non-cognitive outcomes at early stages of exposure. In particular, we look at measures of classroom effort, disruptive behavior, peer support, and risky behavior. The diversity of intermediate outcomes analyzed is also relevant to explore the black box of gendered peer effects and provides valuable inputs for the design of effective policies aimed at closing gender gaps throughout educational trajectories.

The remainder of the paper is structured as follows. Section 2 describes the context and the different sources of data used. Section 3 presents the research design. Section 4 presents the empirical strategy. Section 5 presents the results. Section 6 discuss possible mechanisms at play and Section 7 concludes.

2 Context and Data

2.1 Context

Schooling in Mexico City, the largest school district in the country, is organized in four levels: preschool (from age three to kindergarten), elementary or primary school (grades one to six), middle or secondary school (grades seven to nine) and high school, which has a typical duration of three years.

Secondary education in Mexico is provided through two types of schools: general and technical. The general track is relatively more academically oriented and is focused on preparing students interested in continuing their studies into tertiary education. Technical schools cover most of the same curriculum used in the general track, but they also provide training in specific, hard skills. Mexico's educational system also offers a high school vocational track that focuses exclusively on training students to become professional technicians.

The choice of high school track has important implications for labor market trajectories and wages. Data from a nationally representative survey for high school graduates aged 18-20 show that, when compared to those who graduated from technical or vocational high schools, those who attended general track schools in the metropolitan area of Mexico City are 34 percentage points more likely to enroll in a tertiary education institution and 9 percentage points less likely to work after graduation.[2] Similarly, data from a nationally representative survey of individuals aged 26-35 in urban Mexico show that attending the general track yields a positive premium on average hourly wages equivalent to 12 percentage points above the wages of those who were enrolled in other tracks.[3]

A salient feature of Mexico City is that students are assigned to public middle and high

[2] See National Labor Survey of High School Graduates (ENILEMS, 2012).
[3] See National Labor and Education Survey (ENTELEMS, 2008).

schools via two separate centralized allocation mechanisms. Students who want to attend a public middle school go through a placement mechanism that admits about 140,000 students in 780 secondary schools. Graduating students from elementary schools apply in two steps. They first submit a registration form with basic demographic characteristics and a rank order list of up to three preferred schools. A few months later, all applicants take a standardized test that determines their priority ranking in the placement algorithm. Assignment is done based on a Boston mechanism.[4] Unplaced students at the end of the allocation process are assigned to a school with available seats located near the top school in the candidate's submitted ranking.

Similarly, to request admission to a public high school, students go through another centralized allocation mechanism that admits close to 240,000 students to about 630 schools in the metropolitan area of Mexico City.[5] Graduating middle school students apply to the system at the end of ninth grade by submitting a registration form and taking another placement exam. The centralized admission system is implemented such that students are the main point of contact in terms of communications and the delivery of informational material. The preference form is filled out and submitted by the applicant herself. Students' rank order list can include up to 20 schools. The standardized placement test again serves as the key determinant of admission to each applicant's preferred school. Placement into high school is determined by a matching process based on a deferred-acceptance algorithm.

High school applicants' bids for a seat in their rank order lists are solely based on their placement score. Thus, applicants may end up being misplaced after the deferred acceptance algorithm is implemented if their scores were too low given the competition they faced for their preferred options. In practice, the matching algorithm performs quite well: only 11% of the applicants in our sample remain unplaced in the first round of the matching process.

Unplaced applicants can request admission to other schools with available seats after the allocation process is over or search for a seat in schools with open admissions outside the system (including private schools). Whenever applicants are not satisfied with their placement in the first round (i.e., the implementation of the centralized algorithm), they can request admission to another school in the same way unplaced applicants do. Notice that placement through the second round is not a desirable outcome as it will almost surely imply

[4] The Boston mechanism is implemented as follows: In an initial round, all students compete for their first choice based on their score in the standardized test. Those who are not assigned move on to the next round and compete for their second choice. The process is repeated a third time for students who are still unmatched to a school. In each round, ties are broken by giving preference to those applicants who are younger, those who live closer to the school, and those who have a sibling enrolled in the school at the time of the application.

[5] The metropolitan area around Mexico City includes a number of nearby municipalities that belong to the State of Mexico.

being placed in a school not included in the student's original ranking.

Both centralized placement systems allocate seats in public schools only. Therefore, we cannot assume that a student who decides not to apply is dropping out of school. While this is certainly one possible explanation, students may also fail to participate in the process because they move to other areas of the country, or because they prefer to attend a private school. The choice of private schooling is less of an explanation during middle school, when only nine percent of enrolled students attend private schools, than in high school, when the private sector's share of students increases to 19 percent [INEE, 2019].

An important consequence of the centralized allocation mechanisms is that most students in the entering cohorts meet their peers for the very first time at the beginning of each educational level.[6] Once students are placed into schools, allocation into classrooms is determined by principals or by the school's administrative staff. Even though the schools have access to students' past records and grades of the entrant cohort, there is no centralized instruction or rule to group the students into their classes. Indeed, most schools seem to supervise the composition only to ensure that classes are balanced both in terms of gender and the share of students with special needs.

Both during middle and high school, Mexican students in public schools attend all their classes together. This means that, once students are allocated to groups, there is a close interaction with peers throughout the academic year and for all courses. Moreover, as discussed in Section 3, this initial class assignment carries on to the second and third year of secondary school.

2.2 Sample

Busso and Frisancho [2021] implement a large-scale randomized control trial to evaluate the role of different classroom formation strategies on educational outcomes during middle school. That study relies on a sample of 171 schools randomly selected from the universe of 780 public middle schools in Mexico City.[7] We rely on the subsample of schools that were assigned to the control group. In those schools, once the centralized placement process into

[6]Students placed in our sample of 50 middle schools in Mexico City come from 1384 elementary schools. The average classroom in our sample has 35 incoming students who graduated from 17 different elementary schools. (The minimum number of elementary schools feeding a class is three and the maximum is 33.) As a result, the average student in our sample attends a class in which 94 percent of her peers have attended a different elementary school. The remaining six percent of their peers did attend the same elementary school, but we lack data to determine whether these students were classmates in the past or whether they knew each other.

[7]After excluding schools that were top performers, small schools, schools with a low dispersion in the admission test score, and schools with a relatively high share of students who had special needs, the final eligible universe included 452 middle schools. Treatment assignment was clustered randomized, resulting in 57 schools in the control group.

middle schools was completed –and, therefore, the school population was established– we randomly allocated students to classes. Section 3.3 provides evidence of this randomization. Our analysis sample consists of 50 schools with a total of 271 classes and 9,627 entering middle school students, 4,686 of which were girls.[8]

Table 1 compares the 50 schools in our sample to the universe of middle schools in Mexico City. In general, our sample is very similar to the universe. The majority of average characteristics we check are not statistically significantly different between the two groups. We only find very small differences in terms of the average age (and correspondingly, differences in the proportion of students age 13 or above) and the share of students with special needs.

Table 1: Sample Representativeness
(Schools' Average Characteristics)

	Universe of schools (1)	Experimental sample (2)	p-value of difference (1)-(2) (3)
Age	11.82	11.79	0.01
Attended kindergarten	0.73	0.74	0.62
Lives with both parents	0.64	0.64	0.80
Raw baseline exam	27.07	26.70	0.67
Special needs student	0.04	0.03	0.00
Years of educ., father	10.08	10.16	0.62
Years of educ., mother	9.84	9.95	0.47
Number of schools	780	50	-

Notes. The p-value estimated here is calculated using an OLS estimator at the school level, in a regression with N=830 schools. This sample is the result of the 780 schools, which comprise the universe of secondary schools in Mexico City, and we duplicate the 50 schools in our sample to regress the outcome variables on an indicator variable that is equal to one for the duplicated schools (50) and zero for the complete universe of schools in Mexico City (780). The outcomes are the school averages of the students in placed in each school by the Education Secretary in August 2015. Standard errors are robust.

2.3 Data

Our analysis relies primarily on information coming from the application forms and the administrative records of both the middle and high school placement mechanisms. The administrative records collected by each placement mechanism contain basic students' demographic characteristics, past grade point averages (GPAs), rank order lists, standardized placement test scores, and final placement outcomes (i.e., which middle school and high

[8] From the set of 57 schools in the control group of Busso and Frisancho [2021], we exclude seven schools that exhibit a disproportionate share of students from either sex in the entering cohort. Since randomization of students to classrooms was done for each school, the validity of random assignment is preserved.

school students were assigned to). We also use administrative records of the test score placement cutoffs observed for each high school. Because we study a sample of students from the cohort who started middle school during the 2015-2016 academic year, this information corresponds to the placement round in which most students who graduated from middle school on time should have applied to secure a place in a public high school. The equilibrium score cutoffs for each school allow us to proxy schools' selectivity both in terms of students' submitted preferences and their placement outcomes.[9]

The placement exam taken at the end of elementary school is designed to measure students' academic readiness for middle school. It evaluates three domains: literacy (reading comprehension and writing), mathematics (arithmetic and geometry), and abstract reasoning. The test includes questions of varying difficulty. It is a multiple choice exam that consists of 60 questions worth one point each, without negative marking. The placement exam taken at the end of middle school is broader. It exam consists of 128 questions which assess aptitude and knowledge of math, language, history, geography, ethics, chemistry, biology, and physics.

Table 2: Comparison of Classrooms in the Analysis Sample and the Survey Sample

	Experimental sample (1)	Survey sample (2)	p-value of difference (1)-(2) (3)
Age	11.77	11.75	0.18
Female	0.49	0.49	0.63
Lives with both parents	0.64	0.65	0.44
Special needs student	0.02	0.02	0.42
Std. baseline exam	-0.06	-0.05	0.33
Std. primary GPA	-0.03	-0.04	0.79
Years of educ., father	9.94	9.88	0.80
Years of educ., mother	9.22	9.17	0.88
Number of schools	271	149	-

Notes. p-value estimated using an OLS estimator at the school-group level, controlling for school fixed effects. Standard errors are robust.

We administered two additional standardized exams at the end of 7th grade and 8th grade. These exams were designed by the Ministry of Education and modeled after the middle school entry exam. We also asked students taking the 7th grade exam to fill out

[9] Data on students' submitted preferences were provided at the school level. About 23 percent of the schools, however, offer multiple programs (each one with its own specific cutoff). We define our measure of school selectivity by the average cutoff of all programs within each school. A variance decomposition of the cutoff at the school and program level shows that the average cutoff is a good measure of selectivity at the school level. The overall variance of the school-level cutoff is 19.33. The variance between schools is 20.80; the variance within schools is 5.29.

a questionnaire: a survey designed to collect information on students' behaviors. Due to budgetary restrictions, the exam and the survey were only administered to three randomly chosen classes in each school, covering 149 groups with 4,333 students (boys and girls).[10] Table 2 compares groups in the survey sample to those in the full estimation sample, and shows that there are no statistically significant differences across them.

The analysis also relies on data of the students' middle school outcomes. We observe cumulative GPAs at the end of 7th and 9th grades. We also know which classroom each student attended each of the three years of middle school and therefore we know who their peers were. In addition, these data allow us to measure the persistence over time of the class groupings that we engineered at the beginning of middle school.[11]

2.4 Explanatory Variables

Our main goal is to study how the exposure to high-achieving male and female peers during middle school shapes girls' academic outcomes at the beginning of high school. We identify high performers in our data using the placement exam taken to gain admission to middle school. This allows us to avoid a reflection problem: Applicants' take this exam while still in elementary school, before they have actually met their peers in middle school. Using the distribution of scores in the universe of applicants for the 2015-2016 academic year, we define high performers as those who score in the top 25 percent.

We construct the share of high-performing female students and the share of high-performing male students relative to their peers of the same sex for each entering class.[12] For each student i in the sample, we define F_{ics} and M_{ics} in 7th grade as the fraction of female and male high achievers in the classroom at the beginning of middle school. These shares are constructed as the first moments of the leave-one-out distribution of classroom peers in 7th grade who score in the top 25 percent in the middle school entry exam.

The definition of the main explanatory variables is motivated by several previous studies. We follow Cools et al. [2020] when defining our main independent variables but, while they rely on parental education as a proxy to identify high-achieving peers, we observe actual individual performance in a high stakes exam prior to exposure to middle school peers.

The definition of the treatment variables is also closely aligned to Mouganie and Wang

[10]In two schools, only two groups were surveyed; one of these schools only has two classrooms. In another school, four classrooms were surveyed. In all other schools, three groups were surveyed.

[11]These administrative records were provided by the institution that centralizes middle school records of all secondary public schools in Mexico City, CDIAR (Centro de Desarrollo Informático Dr. Arturo Rosenblueth).

[12]Alternatively, the share of high-achieving students could be defined relative to the whole classroom. As we discuss later in Section 5, results are very similar when we use that alternative definition.

[2020], who focus on the proportion of female high performers relative to all high-performing students in the school cohort at the beginning of high school. In their robustness checks, they also rely on alternative shares, separately defined by sex, as top female and male performers proportional to all students, as well as proportional to students of same sex. The authors define high-performing students based on individual performance in the national high school entrance exam, but they only focus on the math portion because their focus is exclusively on STEM-track choices of students in high school.

Zölitz and Feld [2018] measure the effect of the average performance of male and female peers in the classroom on labor market outcomes. They rely on students' college GPAs, calculated immediately prior to assignment to a section. However, because their identification strategy exploits consecutive section assignments during the trajectory of students in the same college, their treatment measure could be affected by exposure to peers encountered in previous groups. Moreover, their specification was not designed to capture the effect of the distribution of high achievers by sex in the classroom.[13]

2.5 Outcome Variables

We first focus on the impact of good peers on the probability of girls to apply to high school. We then look at placement during the first round of the school assignment algorithm, which is a far more preferable outcome than moving onto the scramble round and getting placed in a school that was not included in the student's original ranking. We also analyze the impact of good peers on the selectivity of the placement school (as measured by its cutoff score) and on the probability of being assigned to an academic school.[14]

Since placement depends both on students' individual performance in the exam as well as on their preferences, we dig deeper into the effects of peers on placement outcomes, and evaluate the role of these two potential channels. In the case of preferences, we construct several indicators based on the submitted rank order lists. We characterize the demand for selective schools through the average last-year cutoff of the schools listed as well as the coefficient of variation of the cutoffs of the choices included in the portfolio. In addition, we evaluate students' preferences for academic alternatives through the share of academic schools in the portfolio.

Access to rich administrative and survey data sources provide us the opportunity to further explore the dynamic gendered peer effects on girls' achievement during middle school.

[13] Two sections can have similar average performances for boys and girls, but show a different concentration of high achievers of each sex.

[14] The nature of our data allows us to observe high school placement outcomes only for the subset of students who apply to high school. In Subsection 5.1 we discuss the implications of this feature of our data, in terms of potential selection and attrition issues, for the interpretation of our results.

We evaluate the evolution of performance between middle and high school using the scores of the standardized exams we applied at the end of 7th and 8th grades. Keeping in mind the potential grading issues that emerge when comparing GPAs across schools, we also evaluate the effect of good peers on 9th grade cummulative grades.

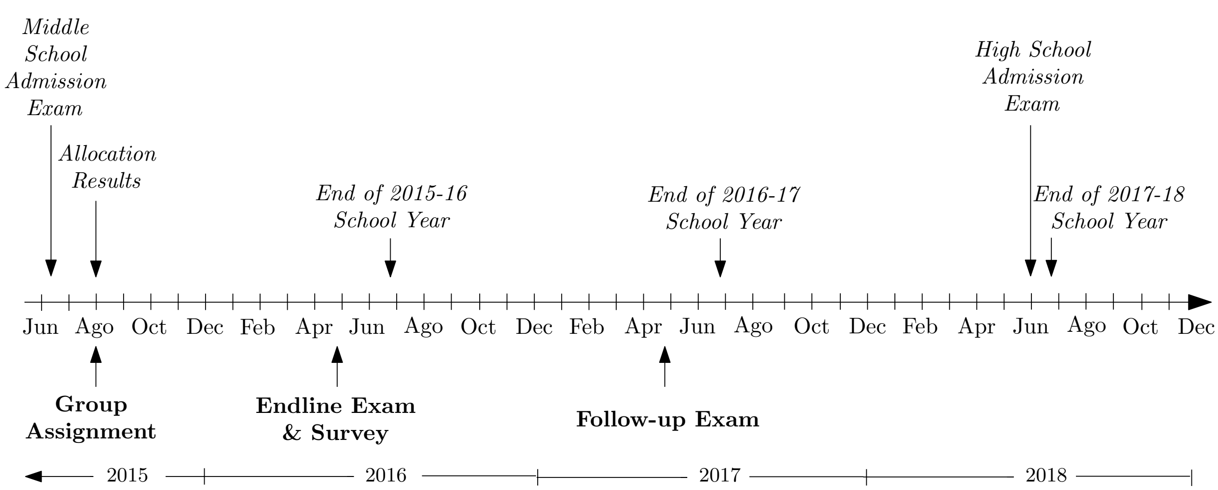
We also rely on survey data to measure the effect of good peers on non-cognitive outcomes at early stages of exposure. In particular, we look at measures of classroom effort (self reported and recorded through absences), disruptive behavior, peer support, and risky behavior.[15]

3 Research Design

3.1 Timeline of events

Figure 1 below presents the timing of both the intervention activities (in italics) and the fieldwork activities (in bold) that took place between 2015 and 2018. We embed the randomization of students to classrooms following the placement of students of schools during the 2015 round of the middle school centralized allocation mechanism. We apply an endline standardized exam and survey at the end of 7th grade (2015-2016 school year) and a second standardized exam at the end of 8th grade (2016-2017 school year). Students are expected to graduate from middle school in the 2017-2018 academic year and, while still in 9th grade, apply for admissions to public high school.

Figure 1: Study Timeline



[15]See Appendix Table A.1 for more details on these scales as well as all the other outcome measures.

3.2 Compliance with Group Assignment

The Ministry of Education distributed the (randomized) classroom assignment lists were distributed to school principals by before the academic year 2015-2016 started. In 7th grade, 94 percent of the students were seated according to those lists. Since we did not provide further instructions to the schools in the sample after 7th grade, it is expected that class composition varied relative to the initial allocation. However, classroom stability remains modestly high: on average, 67% and 49% of students in 8th and 9th grade, respectively, were found in their original class assignment.

One advantage of our setting is the sustained and intensive exposure to peers faced by students in our sample. First, students in Mexico spend all their school day with the same peers, irrespective of the course. Second, the random allocation that we instrumented in 7th grade partially survives throughout middle school.

Table 3 shows that the sustained stability of the groups translates into persistence of the share of high achievers by sex in each classroom. Columns (1)-(4) show that the 7th-grade share of high-achieving girls and boys at the classroom level has a very high correlation with the corresponding shares in 8th and 9th grades. Persistence of class formation suggests that the effects we measure on high school placement outcomes, performance, and preferences cannot be exclusively attributed to first-year exposure to high-achieving peers. For this reason, we interpret our estimates as the treatment effect of being exposed to high-achieving peers *throughout* middle school.

Table 3: Persistence in the Exposure to Good Peers

	8th Grade		9th Grade	
	Share high achieving girls (1)	Share high achieving boys (2)	Share high achieving girls (3)	Share high achieving boys (4)
Share high achieving girls	0.792	-0.046	0.641	-0.036
(7th Grade)	[0.059]***	[0.054]	[0.076]***	[0.064]
Share high achieving boys	0.046	0.889	0.068	0.704
(7th Grade)	[0.043]	[0.059]***	[0.060]	[0.091]***
Number of Classrooms	266	266	259	259

Notes. * significant at 10%; ** significant at 5%; *** significant at 1%. School fixed effects. Robust standard errors. The number of classrooms in the 8th (N=266) and 9th (N=259) grades are smaller than the number of classrooms in 7th grade (N=271) due to the fact that some classrooms were closed and others were merged in later grades.

3.3 Randomization Checks

To verify the validity of our identification strategy, this section provides extensive randomization checks that confirm that the random allocation of students to classes was adequately implemented.

First, we test whether the group/classroom indicator variables jointly predict students' pre-treatment characteristics. If schools had assigned students to classroom based on some observable characteristics then these indicator variables would be statistically significant. Notice that because we have access to the full administrative records, our information set is the same as the one the principal had when these students entered their schools. Following Zölitz and Feld [2018] for each school in our sample and each pre-treatment characteristic, we estimate a regression model on group/classroom indicator variables and compute the F-test of their joint statistical significance. Under random assignment, the F-test should reject the null hypothesis that all the coefficients are zero (i.e., no relation between classroom assignment and students' pre-treatment characteristics) at the five and one percent significance levels, approximately five and one percent of the of the times. Moreover, the p-values of these F-tests of these regression models should be uniformly distributed with a mean of 0.5.

Table 4: Randomization Check 1
Is classroom assignment correlated with students pre-treatment characteristics?

	Percent of classroom fixed effects significant at:			Mean p-values
	5%	1%	0.1%	
	(1)	(2)	(3)	(4)
Age	0.040	0.020	0.000	0.467
Female	0.000	0.000	0.000	0.568
Lives with both parents	0.060	0.060	0.000	0.449
Special needs student	0.022	0.000	0.000	0.341
Std. baseline exam	0.060	0.000	0.000	0.553
Std. primary GPA	0.040	0.020	0.000	0.515
Years of educ., father	0.020	0.000	0.000	0.423
Years of educ., mother	0.060	0.020	0.000	0.481

Notes. This table is based on separate OLS regressions for each school with age, special needs (indicator variable), lives with parents (indicator variable), parent with secondary or more (indicator variable), standardized score for middle school entry, female, and standardized primary GPA as dependent variables. The explanatory variables are a set of group dummies. *Estimation sample:* All students at the of 7th grade.

Table 4 presents the results from this analysis. Columns (1)-(3) show the percentage of schools in which, based on the F-test, the null hypothesis is rejected at the corresponding level of significance (5%, 1%, or 0.1%). Column (4) reports the averages of the p-values of the F-tests for each student's characteristic. These results reflect that, conditional on school assignment, allocation to classes was randomized in our analysis sample.

Second, we present an alternative randomization check that tests whether pre-treatment individual characteristics are correlated with those of peers. Following Guryan et al. [2009], we estimate a regression model for each individual pre-treatment characteristic on (leave-one-out) classroom averages and implement the authors proposed solution when the set of individuals from which peers are drawn –the assigned middle school in our case– is relatively small. Since the bias arises due to the fact that each individual's peers are randomly selected from different populations with a given mean, the authors proposed solution is to control for the average in the reference group (i.e., the school).

Table 5 presents the results from this modified randomization test in our sample of 50 schools. We fail to identify significant correlations between individual and group measures for most of the other pre-treatment characteristics. We only identify a small positive correlation in the case of elementary school GPA and a negative correlation for father's years of education. Importantly, we do not find evidence of any systematic correlation between individual initial performance and peers' initial performance as measured by the middle school admission exam. Because the shares of high achievers are constructed based on the distribution of this score in the classroom, these results support our identification strategy.

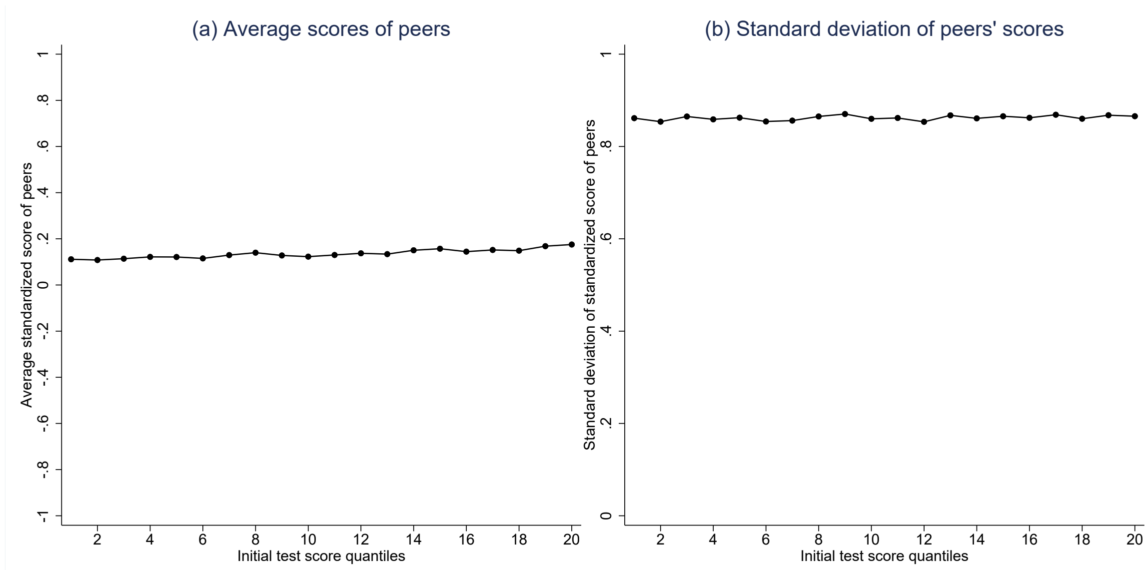
Table 5: Randomization Check 2
Are individual characteristics correlated with average classroom characteristics?

Panel A: Background variables					
	Lives with both parents (1)	Years of education (father) (2)	Years of education (mother) (3)	Household size (4)	
Group average	-0.002	-0.082	-0.005	0.010	
	[0.032]	[0.047]*	[0.031]	[0.027]	
Observations	9278	7721	9627	9278	
Panel B: Individual variables					
	Age (1)	Special needs (2)	Repeater (3)	Std. baseline exam (4)	Std. Primary GPA (5)
Group average	-0.006	0.013	-0.022	0.037	0.065
	[0.023]	[0.019]	[0.049]	[0.023]	[0.022]***
Observations	9627	9627	9627	9627	9338

Notes. * significant at 10%; ** significant at 5%; *** significant at 1%. Reported coefficients are obtained from an OLS regression model that includes the leave-one-out group average of each outcome as well as the leave-one-out school average of each outcome (not reported), following Guryan et al. (2009). *Estimation sample:* All students at the beginning of 7th grade. We also include school fixed effects. Standard errors are clustered at the school-group level.

Figure 2 further reinforces this point. We report the mean and the standard deviation of the initial score of a student's classmates as a function of the student's own initial score in our analysis sample. Because schools vary in terms of their initial ability distribution, we standardize exam scores within school before computing the mean and the variance in the classroom –this is analogous to adding the school averages as controls in Table 5. Panel (a) confirms that the average score of peers is not correlated with student's own score, while Panel (b) shows that the random allocation of students to classes in also leads to a flat function between the variance in peers' ability and own ability.

Figure 2: Peer's Academic Achievement Distribution



Notes. Each dot plots the leave-one-out average (Panel A) and standard deviation (Panel B) of classroom peers middle school admission exam score in a given 20-quantile. *Estimation sample:* All students at the beginning of 7th grade.

After providing evidence that group assignment was implemented according to randomization, we next verify that in the sample of girls, the share of high achieving boys and girls are not correlated with individual characteristics. Table 6 below reports the coefficients of an OLS regression of students' pre-treatment characteristics (in columns) on the share of high-achieving girls and boys. The results show that individual characteristics are balanced across different intensities of high achievers of both sexes. Despite a few statistically significant correlations for the case of maternal education and elementary school GPA, the distribution of characteristics is balanced with respect to the shares of high-performing peers. Despite this, we control for the pre-treatment variables included in Table 6 in our main specification.

Table 6: Balance of Observable Characteristics

Panel A: Background variables	Lives with both parents (1)	Years of education (father) (2)	Years of education (mother) (3)	Household size (4)	
Share high achieving girls	0.007	-0.073	-0.224**	0.031	
	[0.013]	[0.086]	[0.092]	[0.063]	
Share high achieving boys	0.011	-0.005	-0.021	-0.052	
	[0.013]	[0.082]	[0.086]	[0.051]	
Observations	4527	3766	4686	4527	
Panel B: Individual characteristics	**Age (1)**	**Special needs (2)**	**Repeater (3)**	**Std. baseline exam (4)**	**Std. Primary GPA (5)**
Share high achieving girls	0.013	0.001	0.001	-0.013	-0.022
	[0.017]	[0.003]	[0.002]	[0.018]	[0.022]
Share high achieving boys	0.008	-0.000	0.001	0.000	-0.046**
	[0.015]	[0.003]	[0.001]	[0.021]	[0.023]
Observations	4686	4686	4686	4686	4562

Notes. This table is based on separate OLS regressions for each school with age, special needs (indicator variable), lives with parents (indicator variable), parent with secondary or more (indicator variable), standardized score for middle school entry, female, and standardized primary GPA as dependent variables. The explanatory variables are a set of group dummies. *Estimation sample:* All girls at the beginning of 7th grade.

3.4 Variation in Explanatory Variables

The random allocation of students to classrooms led to large variations in the share of high-achieving boys and girls across classes within the same school. Table 7 shows the (leave-one-out) distribution in high achievers, by sex, encountered by girls in our sample. The table reports the mean, the standard deviation, and the range of the proportion and number of high achievers. In each case, we report these statistics with and without school fixed effects.

On average, about 20 percent of the classroom (or about 3.7 students) are high achievers.[16] The standard deviation is 0.16 (or 3.3 students). After removing the school fixed effects, the standard deviation of the proportion of high achievers is cut in half to 0.08 (or 1.6 students), but it is still considerable. This degree of variation is, for instance, similar to the one exploited by Cools et al. [2020].

[16]High achievers are defined as those above the 25th percentile of the universe of applicants to middle school. Because the shares of high-performing female and male students are measured in each classroom in our sample, we expect the average shares of high achievers by sex to differ from 0.25.

Table 7: Variation in the Share of High-Achieving Girls and Boys

	Share high achieving girls (1)	Share high achieving boys (2)	Number high achieving girls (3)	Number high achieving boys (4)
Raw Variables				
Mean	0.20	0.19	3.84	3.62
s.d.	0.16	0.16	3.42	3.32
[Min, Max]	[0.00, 0.81]	[0.00, 0.71]	[0.00, 16.00]	[0.00, 15.00]
Net of school fixed effects				
Mean	0.00	0.00	0.00	0.00
s.d.	0.08	0.08	1.57	1.63
[Min, Max]	[-0.26, 0.26]	[-0.20, 0.26]	[-5.04, 4.17]	[-4.91, 6.45]
Observations	4686	4686	4686	4686

Notes. High achievers defined as being over the 75th percentile of the complete baseline exam distribution for 2015. *Estimation sample:* All girls at the beginning of 7th grade.

4 Estimation Strategy

To measure the impact of female and male high performers on girls' educational trajectory, performance, preferences, and behavior, we estimate the following model:

$$Y_{ics} = \alpha + \beta_1 F_{ics} + \beta_2 M_{ics} + \gamma_1 F_{ics} S_{ics} + \gamma_2 M_{ics} S_{ics} + \delta X_{ics} + \epsilon_s + \epsilon_{ics} \tag{1}$$

where Y_{ics} denotes the outcome of interest of student i in classroom c in school s. There are two independent variables of interest that capture the classroom composition: F_{ics} and M_{ics}, which denote the fraction of female and male high achievers in the classroom, respectively. Both F_{ics} and M_{ics} are the first moments of the leave-one-out distribution of classroom peers who score in the top 25 percent in the middle school entry exam. In our analysis, F_{ics} and M_{ics} are standardized to have a mean of zero and a standard deviation of one.

Because the role of high-achieving peers may vary depending on the initial ability of the student, we interact these shares with S_{ics}, the student's standardized performance in the middle school admission exam, which is taken at the end of primary school, in the transition into middle school. X_{ics} is a vector of controls including S_{ics}, age, an indicator variable equal to one if the student has special needs, mother's years of education, an indicator variable for whether the student had no entry exam score, initial classroom rank based in S_{ics}, and the proportion of girls in the class. Because the randomization of students into classes takes place once the student is allocated into a middle school, we also include school fixed effects (ϵ_s). The unit of randomization was the student, but F_{ics} and M_{ics} are highly correlated within the classroom. For that reason, we cluster standard errors at the classroom level.

5 Results

At the end of middle school, students go through a centralized process (discussed in Section 2.1) that places applicants into high schools and determines much of their future academic career, as well as their labor market outcomes later in life. Since high school placement will determine the beginning of students' trajectories in upper secondary schools and beyond, we first focus on students' performance during the application process, and we then disentangle between the effects of potential channels.

5.1 Probability of Applying to High School

Table 8 shows the estimated coefficients of regression models corresponding to equation (1). In the first column, the dependent variable measures the probability of registering to take the placement high school exam as a function of the shares of high-achieving girls and high-achieving boys, but without adding the interaction with initial score. The second column, our preferred specification, includes these interactions.

Table 8: Treatment Effects on Girls' Probability of Applying to High School

	(1)	(2)
Share high achieving girls	-0.004	-0.005
	[0.010]	[0.010]
Share high achieving boys	0.006	0.010
	[0.011]	[0.012]
Share high achieving girls × baseline score		0.002
		[0.008]
Share high achieving boys × baseline score		-0.012
		[0.008]
Observations	4686	4686

Notes. OLS estimator using student demographic variables as controls, school fixed effects, and clustered at the school-group level standard errors. Registers to high school is defined as one if the student registered with COMIPEMS and took the high school placement exam. *Estimation sample:* All girls at the beginning of 7th grade.

The results in Table 8 suggest that a higher exposure to good peers do not affect girls' probability of applying to high school. Moreover, these effects are homogeneous along the baseline exam score distribution. An important implication is that there is no sample selection into the centralized mechanism based on the share of high-performing peers of either sex. [17]

[17] In the case of boys, exposure to higher shares of high-achieving girls and high-achieving boys leads to a greater probability of applying to high school. Because observing many of the outcomes of interest requires that students are indeed applying to high school, this implies a plausible selection that may bias

Notice that our analysis sample in 7th grade consists of 4,686 girls. However, only 3,555 of them took the high school admission exam and 2,906 were admitted to a school in the first allocation round of the centralized mechanism. We found that girls who progress into high school have more educated parents and higher academic achievement, which allows them to secure a seat in one of their preferred schools and avoid the scramble round.[18] However, this positive selection operates across the board and it is unrelated to the treatment; the choice to apply to high school is orthogonal to our explanatory variables, F_{ics} and M_{ics}, as shown in Table 8. A corollary of this result is that treatment is not correlated to the probability of observing girls' admission and placement outcomes (which we analyze in the next sections).

5.2 Effects on High School Admission

How do girls who were exposed to a higher share of high-achieving peers fare in their high school placement outcomes? Figure 3 shows the results of being exposed to high-achieving boys and girls on the probability of being assigned to a high school (top panel) and on the selectivity of the school to which the student was assigned (bottom panel). The figure shows marginal effects that were computed using the estimated coefficients from regression model (1) where the dependent variables were admission to high school and the cutoff score of the placement option, respectively. The left (right) panel shows the marginal effect for girls of increasing the share of high-achieving girls (boys) in the classroom by one standard deviation. The red dotted line marks the score cutoff that corresponds to the 75th percentile in the distribution of baseline exam scores – the threshold achievement level of students who are defined as high achievers.[19]

To simplify the description of the results, we consider girls to be low-achieving if they scored two standard deviations below the average in the middle school admission exam. We find that low-achieving girls who were exposed to a larger share of same-sex high achieving peers improved their placement outcomes. This *protective effect* on low-achieving girls increases their probability of being placed (although the effect is not statistically significant at normal levels), and raises the selectivity of the placement school. A one standard deviation increase in the share of high-achieving girls leads to a 0.15 of a standard deviation increase

the estimates of the effect of good peers on boys' outcomes. For this reason we focus the main analysis on girls. For completeness, we present the results for boys in the Online Appendix, Section 1.

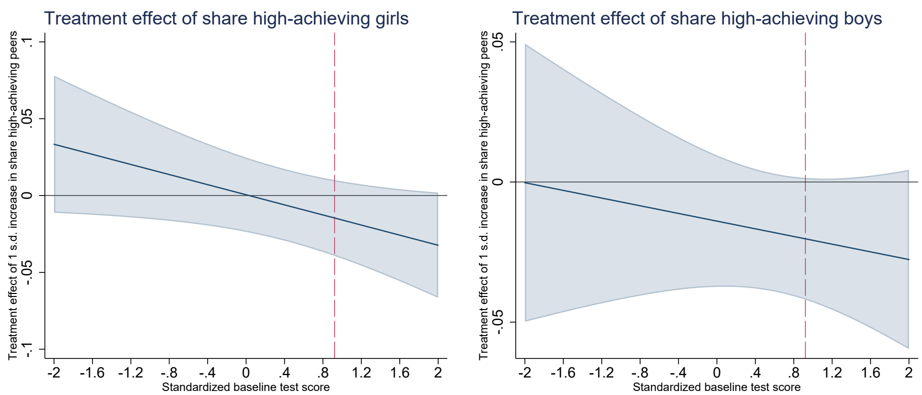
[18] The Online Appendix Section 2 provides detailed information on sample sizes and a description of students' characteristics in each subsample as they progress throughout the educational system.

[19] The estimates behind this and the following figures in Sections 5 and 6 are presented in the Appendix tables A.2, A.3 and A.4. In addition, the Online Appendix Section 3 presents the results without the interaction with the pre-treatment standardized test score. We lack statistical power to reject the null of no average treatment effects for most outcomes under analysis. The only exception is a statistically significant effect of high achievers (of both sexes) on girls' high school entry exam.

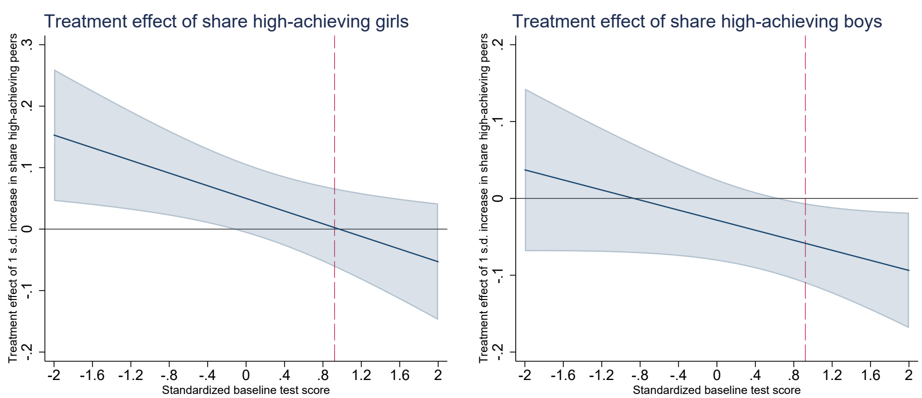
in the selectivity of the placement school of low-achieving girls.

Figure 3: Marginal Effect on High School Admission Outcomes

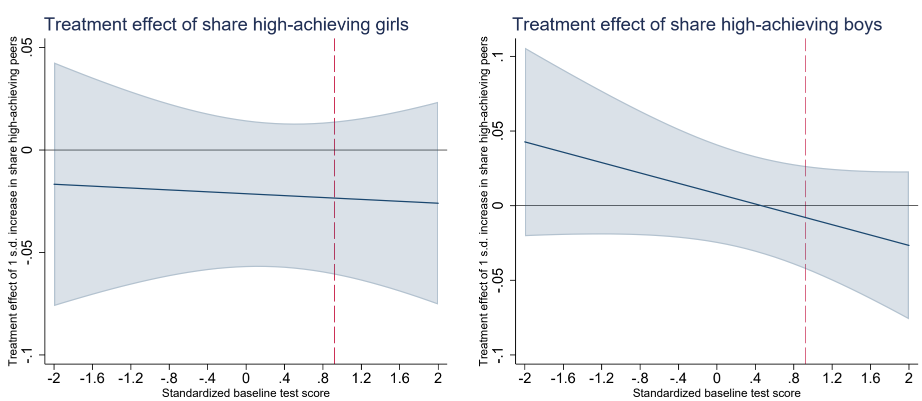
(a) Probability of being assigned to a high school



(b) Assigned high school selectivity



(c) Probability of being assigned to an academic high school



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in 1 with respect to each of the shares. Standard errors are calculated using the Delta method. *Estimation sample:* All girls that applied to high school (Panel A) and all girls placed in the first round (Panels B and C).

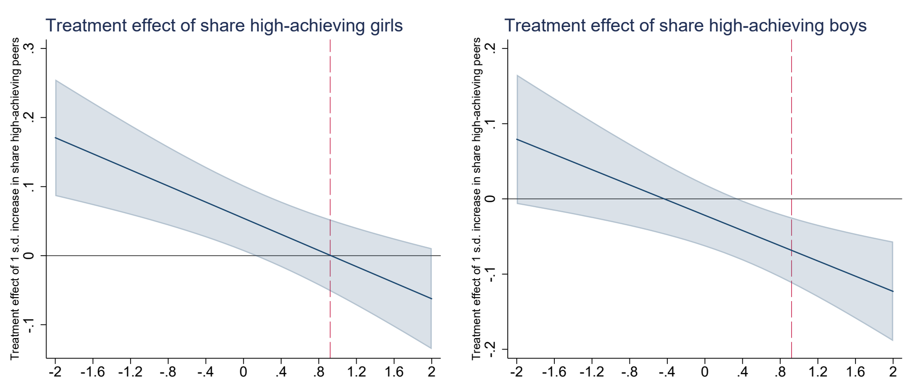
The presence of high-achieving peers, regardless of their sex, hurts high-achieving girls in terms of high school placement outcomes. For girls who score two standard deviations above the average placement score in middle school, an increase of one standard deviation in the share of high-achieving peers decreases the probability of being assigned to a school by a similar magnitude, irrespective of their peers' sex, by about three percentage points. By contrast, the effect of exposure to high-achieving peers is only detrimental in the case of male peers: a one standard deviation increase in the share of high-achieving boys decreases the selectivity of the placement school by almost 0.5 standard deviations for girls who score at least 0.5 standard deviations above average.

5.3 Do Good Peers Affect Academic Achievement or Preferences?

As discussed in Section 2.1, high school placement is exclusively determined by performance in the admission exam and the rank order list of preferences submitted by the student. This setting enables us to dig deeper into the effects of peers on placement outcomes, and to evaluate the role of two potential channels: differential academic performance in the admission exam or changes in preferences.

Academic achievement–. Figure 4 presents the effect of high-achieving peers on performance in the high school placement exam. Such high-performing peers, particularly girls, have an important, positive effect on low-achieving girls' academic performance. This protective effect is equivalent to 0.17 of a standard deviation among low-scoring girls in the middle school placement exam and highlights the importance of female role models [Porter and Serra, 2020].

Figure 4: Marginal Effect on High School Entry Exam



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in 1 with respect to each of the shares. Standard errors are calculated using the Delta method. *Estimation sample:* All girls that applied to high school.

Exposure to high-achieving boys leads to more modest impacts (0.08 of a standard deviation) on the score of low-achieving girls. The impact of good peers, particularly boys, is reversed for high-achieving girls. Female high-performers experience 0.12 of a standard deviation reduction in their score when exposed to a one standard deviation increase in the share of high-achieving boys.

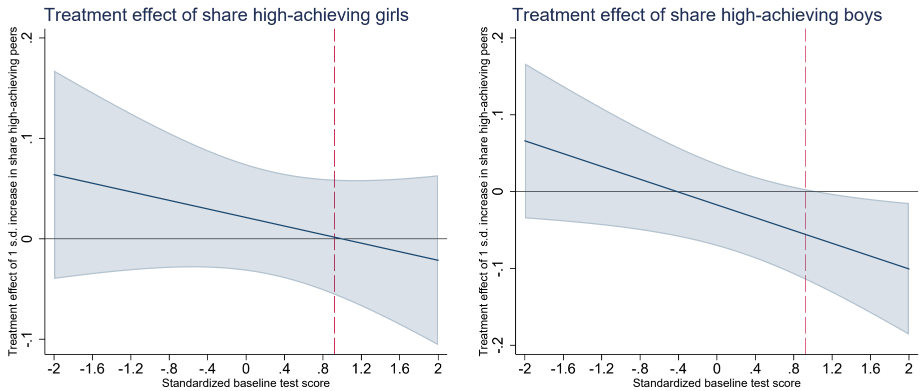
Our results complement the findings of previous studies that focused on the gendered effects of peers on grades. Zölitz and Feld [2020] study the effect of the proportion of female peers on college grades, which are mainly determined by students' end-of-the-year exam scores. Their findings show that men's grades are not affected by the gender composition of their peers, while women's scores increase with exposure to a larger share of women in the groups. However, the protective effect of girls on same-sex peers is present only in non-math courses; by contrast, men benefit from the presence of a high share of females only in math courses. Hoxby [2000] also studies the effect of having a higher share of female classmates on course grades in elementary school. She finds that both female and male students perform better in math when there is a higher share of females in the class. Our results are somehow aligned with these studies: high-scoring girls have a protective effect on the academic performance of same-sex peers, but only among those who start out at a disadvantage. Similarly, Cools et al. [2020] show that exposure to high-achieving males is associated with a negative but statistically insignificant impact on GPAs of girls, whereas high-achieving females have a positive and statistically insignificant effect.

Preferences–. Relying on school equilibrium cutoff scores in the previous placement 2016-17 round, we capture two main attributes of students' portfolios related to selectivity to characterize the effect of high-achieving peers on choices. Very competitive schools have higher minimum entry scores than less competitive ones. We thus focus on the average cutoff and the coefficient of variation of the submitted portfolio as proxies of average selectivity and heterogeneity in preferences.

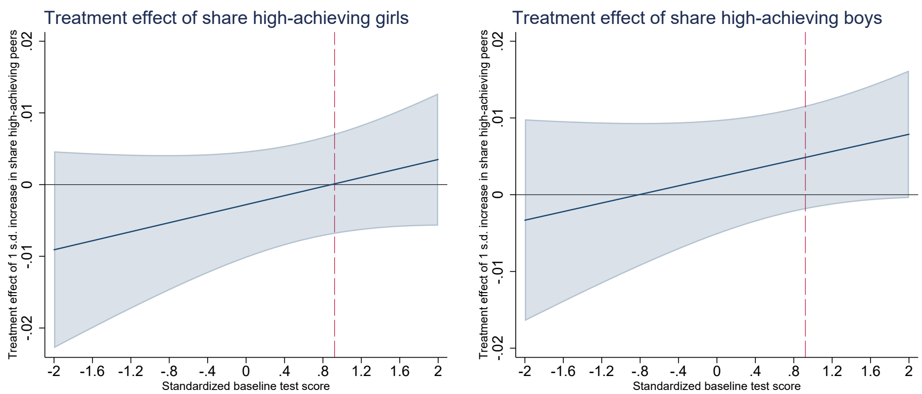
The top panel in Figure 5 shows the effect of high-performing peers on preferred average selectivity. There is no statistically significant effect of high-achieving girls on the selectivity of schools preferred by girls. There is, however, a negative effect of high-achieving boys on high-achieving girls. Among girls who score two standard deviations above the average in the baseline exam, a one standard deviation increase in the share of high-achieving boys reduces the average selectivity of the schools that high-achieving girls aspire to attend; the average selectivity of the rank order list of schools these girls choose declines by 0.10 of a standard deviation.

Figure 5: Marginal Effect on High School Preferences

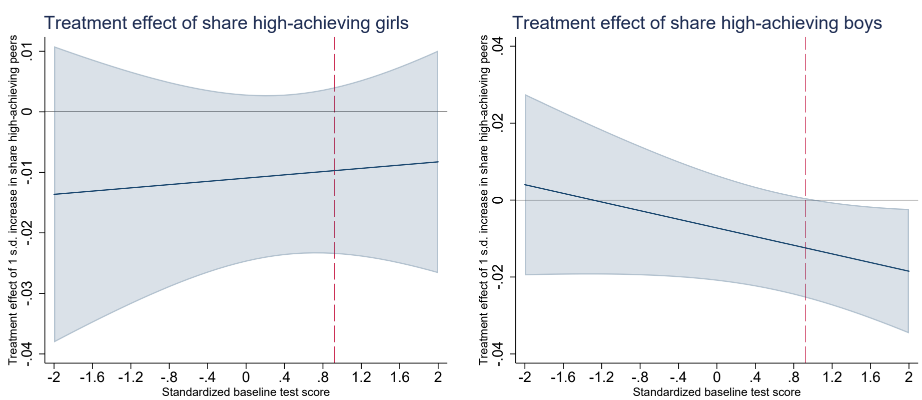
(a) Average high school selectivity in portfolio



(b) Heterogeneity of high school selectivity in portfolio



(c) Share of academic options in portfolio



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in 1 with respect to each of the shares. Standard errors are calculated using the Delta method. *Estimation sample:* All girls that applied to high school.

These results are aligned with Cools et al. [2020], who show that a greater proportion of high-achieving boys negatively impacts girls' self-confidence and stated ambitions to go to college. Since we observe revealed preferences, we can complement their results by studying the effects of good peers on direct measures of aspirations/ambitions. In our setting, students' rank order lists are directly linked to high stakes decisions about future academic trajectories. We consider these data to be more reliable than aspirations measured as individuals' desire to go to college.

Panel (b) in Figure 5 presents the impact on the heterogeneity of high school selectivity in choices. A larger share of high-achieving girls has no effect on girls' preferences, but a larger share of high-achieving boys pushes high-achieving girls to apply to more heterogeneous sets of schools. Conditional on the drop in the mean registered in Panel (a), girls with initially good scores choose schools with more disperse past cutoff scores –a trend that could signal increased risk aversion.

We also look at the impact of high-achieving peers on other dimensions of preferences. For instance, Panel (c) shows null or very small effects of female good peers on the share of academic schools included in the portfolios (as opposed to technical or vocational schools). In turn, high-achieving boys reduce the share of academic options listed by high achieving girls. This suggests that the effect of high-achieving boys on the preferences of high-achieving girls is acting both through an effect on girls' perceptions of their own academic performance as well as through changes in the type of trajectories they choose. The reduced demand for academic high schools is aligned with the negative effects that high performing males have on girls' choices of STEM and male dominated majors in Mouganie and Wang [2020] and Zölitz and Feld [2020], respectively. Our findings suggest that early and focused interventions are important to deter the erosion of high-achieving girls' aspirations, and boost preferences for better-paying fields of study.

All in all, these results confirm that early exposure to male top scorers hurt educational outcomes of high-achieving girls, both through reduced performance at the end of middle school, and via a reduced preference for selective schools. In turn, the protective effect of high-achieving girls on same-sex peers with low performance is only driven by improved scores.[20]

[20] As a robustness check we can define the share of high-achieving students relative to the whole classroom. In the Online Appendix Section 4 shows that the results are very similar when we use that alternative definition.

6 Mechanisms

6.1 Learning: Dynamic Effects

Because the performance of both low- and high-achieving girls is affected by peers, it is natural to ask when these effect start to appear. Do the effects begin early after exposure to high-performing peers, or, instead, do they take time to materialize? We address the question of timing by looking at the dynamic effects of high-achieving peers on girls' performance through the use of additional, standardized exams and cumulative GPAs during middle school.

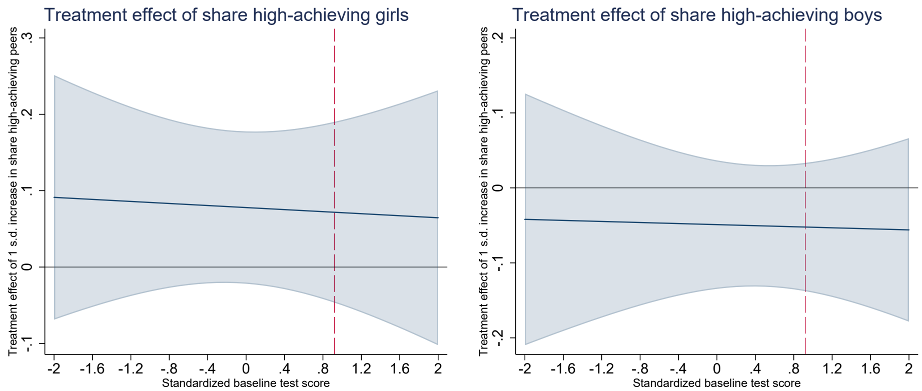
Figure 6 shows the impact of high-achieving peers at the end of each secondary school grade. Panels (a) and (b) depict the effect of good peers in grades seven and eight relying on standardized exams that mimic the admission exam used to regulate placement into middle school in Mexico City.[21] We find no contemporaneous effects of being exposed to high-achieving peers in 7th grade on academic performance, regardless of initial academic achievement. By the end of the 8th grade, however, we start to see a positive effect of high-achieving girls on same-sex, low-achieving peers (although the effect is not statistically significant). We also find that the share of high-achieving boys negatively impact the academic achievement of girls with medium and high levels of initial performance. For medium achievers (students who have a score equal to the average score), a one-standard-deviation increase in the share of high-achieving boys reduces their performance on the 8th grade exam by 0.07 of a standard deviation; the effect on high-achieving girls is also negative, corresponding to a reduction of 0.17 of a standard deviation. These results suggest that, while peers' effects on performance at the end of middle school are not instantaneous, they do start to manifest before girls apply to high school.

Panel (c) shows that the effect by 9th grade (as measured by the standardized GPA) is not statistically significant, although the sign and directions of the marginal effects are similar to those found in 8th grade. Even though we try to normalize GPAs to take into account differences among schools, this results should be take only as informative as they do not correspond to a standardized measure of performance.

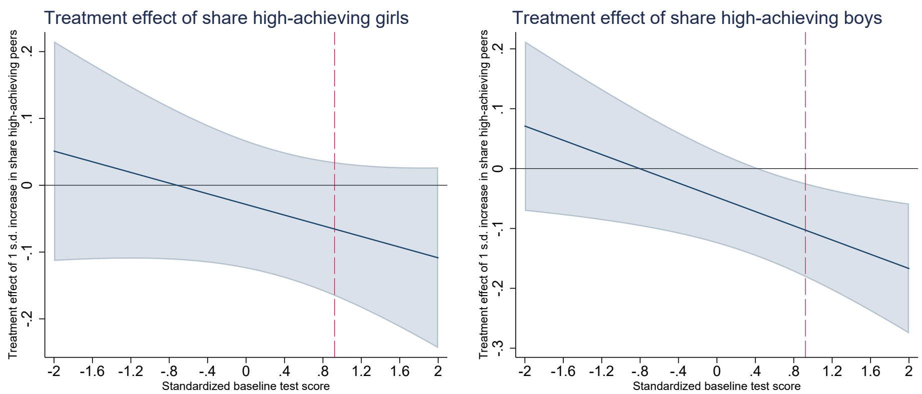
[21] See Section 2.3 for more details on the survey sample.

Figure 6: Marginal Effect on Academic Achievement: Dynamic Effects

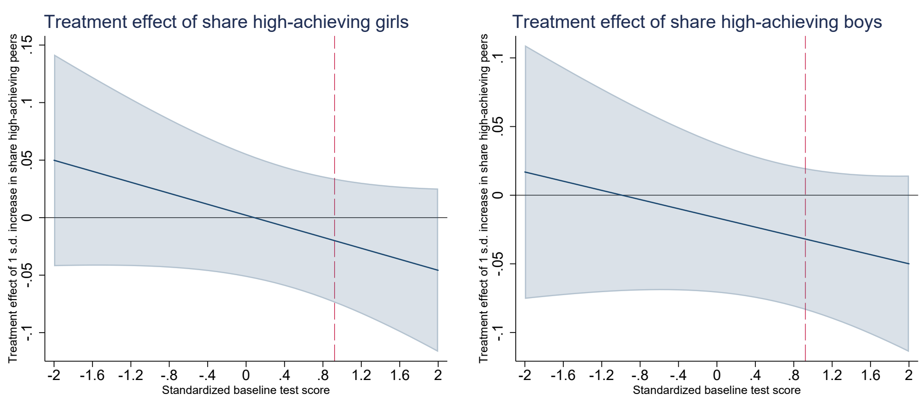
(a) Standardized test scores (7th grade)



(b) Standardized test scores (8th grade)



(c) Standardized grade point average (9th grade)



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in 1 with respect to each of the shares. Standard errors are calculated using the Delta method. *Estimation sample:* Panels A and B refers to a subsample of girls that applied to high school and took the administered standardized exam in 7th or 8th grade (see Section 2 for details). Panel C refers to all girls that applied to high school.

6.2 Student's Behavior

While performance effects are not yet present in 7th grade, other channels may still be activated early on. We present a number of these results in the Online Appendix Section 5. Except for school absenteeism, the analysis of behavior relies on self-reported measures collected in our survey at the end of 7th grade through a set of pre-defined scales.

First, we explore whether peers' influence may be altering girls' effort during 7th grade. One objective measure of effort is school absenteeism. We cannot reject the null hypothesis of no effect on the number of days that girls skip school. In addition, we built an index of classroom effort based on five survey items that ask students if they feel like they work hard and pay attention in class, for example. We find no effects.

Second, we test for effects on peer support (i.e., the level at which students within the class help each other and hope their peers do their best). We find that a larger share of high-achieving girls reduces self-reported peer support among their low-achieving peers.

Third, we are also able to measure in-class disruptive behavior based on other questions that capture, for example, whether the student follows instructions, mocks or purposely annoys the teacher, or interrupts the class. High-achieving girls have no effect on disruptive behavior, while high-achieving boys increase the disruptive behavior of girls, especially for those in the middle of the distribution of initial ability. We also find that a higher exposure to high-achieving boys is associated with riskier behaviors (related to cigarettes and/or alcohol consumption) in high-achieving girls; although these effect is not statistically significant. Finally, we look at self-reported measures of truancy (defined as skipping school without parental knowledge) and school behavioral problems (e.g., whether they were removed from the classroom, engaged in physical fights with classmates, or were suspended from school) and find no effect of good female or male peers on none of these two behavioral outcome measures.

7 Conclusion

Despite considerable reductions in gender gaps in school enrollment and graduation rates, labor market disparities in occupations and wages across men and women persist. To narrow these gaps, it is important to understand the origin of the forces that drive them. The literature has identified how women and men differ across perceived socio-emotional traits and psychological attributes. Even though the evidence is not conclusive on whether these differences are inherent or socially induced [Shurchkov and Eckel, 2018], they can influence educational and occupational choices.

Our paper sheds light on the asymmetric responses that girls experience from exposure to high-achieving peers of different sexes in middle school. We focus on potential sources of disparities at this stage, a point in time that still presents opportunities to reverse impediments that hinder girls' educational trajectories.

Using standardized scores from the end of elementary school to determine initial academic credentials, we rely on random allocation of students to classes at the beginning of middle school to study the effects of the proportion of high-achieving girls and high-achieving boys, separately, on girls' placement outcomes in high school. Relative to previous studies, our paper poses several methodological, contextual, and data-related advantages. Not only are we able to exploit experimental variation in the allocation of students to classes, but we also do so in a sample of 50 public middle schools in Mexico City. We rely on pre-treatment and standardized measures of performance to determine high-performer status in our sample, thus dealing with the reflection issue present in other peer effects' studies. Furthermore, we use administrative records from the centralized admission exam to get into high school to disentangle between the role of good peers both on girls' academic performance and aspirations. We rely on revealed preferences as a novel approach to accurately measure aspirations. The richness of the administrative and survey data collected during middle school further allows us to explore dynamic grade effects as well as the role of peers on non-cognitive outcomes such as classroom effort, disruptive behavior, peer support, and risky behavior.

We identify asymmetric effects of high-achieving peers depending on their sex. The presence of female top scorers has a protective effect on low-performing girls in terms of the selectivity of the placement school while the presence of better male peers does not affect the outcomes of these low-performing girls. High-achieving peers, particularly boys, hurt the placement outcomes of female high performers.

We find that early exposure to male top scorers hurts educational outcomes of high-achieving girls, both through reduced performance at the end of middle school, and through a reduced preference for selective and academic schools. In turn, the protective effect of high-achieving girls on same-sex peers with low performance is only driven by improved scores.

Importantly, we do not find any evidence of changes in effort, disruptive behavior, or grades during the first year of exposure to high-achieving peers. The influence of peers from either sex only starts to materialize after sustained exposure, during 8th grade. This is potentially good news in terms of presenting a window of opportunity to design timely interventions. Our results suggest that early programs that foster students' socio-emotional development during childhood and adolescence may be helpful to reduce the discouragement effects that male high achieving peers can have on high achieving female classmates. Additionally, professional development activities for teachers that equip them with tools to identify potential negative class dynamics could help prevent (or at least ameliorate) the negative effects that high-achieving boys seem to have on high-achieving girls' motivation and aspirations.

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Appendix Tables

Definition of Variables

Table A.1: Variables and description - Outcome variables

Variable	Description
	Placement outcomes
Assigned to school	Student was assigned to a high-school in the first round. This means that her scores in the high-school entry exam were high enough to allow her to enter one of the schools listed in her preferences.
Cut-off assigned school (selectivity)	Cut-off (or average cut-off if there are several programs in the school) of the student's assigned school. The cut-off is the minimum score of admitted students in the previous year. If a student has a score above the school cut-off and the school is amongst her listed school preferences, she can be assigned to this high-school, otherwise she will be placed in another school.
Assigned to an academic option	Indicator variable equal to 1 if the student is assigned to an academic type high-school (as opposed to a technical or vocational one).
	Preferences outcomes
High-school entry exam	Standardized exam score for every student that signs up and takes the exam for a place in a high-school.
Mean cut-off in preferences	Average cut-off of the schools listed in the portfolio of the student. A students' portfolio lists the schools in a ranked manner in accordance to the student's preferences (her most desired high-school is the first in the list, and so on).
CV of portfolio cut-offs	Coefficient of variation of the cut-offs of the schools in the portfolio of the student.
Share of academic options in portfolio	Share of academic high-schools in the student's portfolio.
	Secondary school outcomes
7th grade exam score	7th grade standardized exam score. The total score is computed by adding up the three test sub-scores: math, literacy and abstract reasoning. This exam was taken in 2016.
8th grade exam score	8th grade standardized exam score. The total score is computed by adding up the three test sub-scores: math, literacy and abstract reasoning. This exam was taken in 2017.
9th grade GPA	Standardized overall GPA in 9th grade. The GPA was calculated as the average of all subject final grades of each student in 2018. We then standardize this average.
	Mechanisms outcomes
Absences (Grade 7)	Logarithm of the average absences reported for the student per quarter.
Classroom effort	Standardized index constructed as follows. We estimate a factor model using the following survey items: working hard, paying attention in classes, understanding difficult problems, time spent doing homework and participating in class activities. These items have a likert scale from 1 (Never) - 4 (Always). The model was estimated using maximum likelihood and imposing one factor. The Cronbach alpha equals 0.712.
Disruptive Behavior	Standardized index constructed as follows. We estimate a factor model using the following survey items: following instructions from teachers in class, mocking teachers during class, having trouble with teachers during classes, interrupting the class, and behaving in a way that annoys teachers. These items have a likert scale from 1 (Never) - 4 (Always). The model was estimated using maximum likelihood and imposing one factor. The Cronbach alpha equals 0.774.
Peer support	Standardized index constructed as follows. We estimate a factor model using the following survey items: helping other students to learn, hoping other students do their best at schoolwork and expecting their peers to come to class every day. These items have a likert scale from 1 (Totally disagree) - 4 (Completely agree). The model was estimated using maximum likelihood and imposing one factor. The Cronbach alpha equals 0.784.
Risky behavior	Standardized index constructed as follows. We estimate a factor model using the following survey items: the student has tried cigarettes and whether the student has tried alcohol. These items have a likert scale from 0 (No) - 1 (Yes). The model was estimated using principal factor due to few variables and imposing one factor. The Cronbach alpha equals 0.516.
School behavioral problems	Standardized index constructed as follows. We estimate a factor model using the following survey items: being told to leave the classroom due to bad behavior, having engaged in a physical fight with a classmate, or having been suspended from school. These items have a likert scale from 0 (No) - 1 (Yes). The model was estimated using maximum likelihood and imposing one factor. The Cronbach alpha equals 0.601.
Truancy	Standardized index constructed as follows. We estimate a factor model using the following survey items: the number of times in the past two weeks that he did not go to school and stayed home without permission, left home for school but went to another place, and went to school but left early without permission. These items have a likert scale from 1 (Never) - 4 (3 or more times). The model was estimated using maximum likelihood and imposing one factor. The Cronbach alpha equals 0.787.

Estimation Results Behind Text's Figures

Table A.2: Effects on Girls' Placement Outcomes (Figure 3)

	Assigned to school (1)	Cut-off assigned school (2)	Assigned to academic school (3)
Share high achieving girls	0.001	0.050	-0.021
	[0.012]	[0.029]*	[0.018]
Share high achieving boys	-0.014	-0.028	0.008
	[0.012]	[0.027]	[0.017]
Share high achieving girls × baseline score	-0.016	-0.052	-0.002
	[0.008]**	[0.021]**	[0.011]
Share high achieving boys × baseline score	-0.007	-0.033	-0.017
	[0.009]	[0.019]*	[0.012]
Observations	3555	2906	2906
Mean	0.817	-0.041	0.461

Notes. * significant at 10%; ** significant at 5%; *** significant at 1%. Administrative data from COMIPEMS. Standard errors clustered at the school-group level. School fixed effects. Control variables used are age, whether the student has special needs, mother's years of education, if the student had no entry exam score, standardized baseline exam score, rank in the class in baseline and proportion of women in the group. *Estimation sample:* All girls that applied to high school (Panel A) and all girls placed in the first round (Panels B and C).

Table A.3: Effects on Girls' Entry Exam Score and Preferences (Figures 4 and 5)

	High-school entry exam (1)	Mean cut-off in prefs. (2)	CV of portfolio cut-offs (3)	Share of academic schools (4)
Share high achieving girls	0.054	0.021	-0.003	-0.011
	[0.024]**	[0.027]	[0.004]	[0.007]
Share high achieving boys	-0.022	-0.017	0.002	-0.007
	[0.021]	[0.027]	[0.004]	[0.007]
Share high achieving girls × baseline score	-0.058	-0.021	0.003	0.001
	[0.016]***	[0.020]	[0.002]	[0.004]
Share high achieving boys × baseline score	-0.051	-0.042	0.003	-0.006
	[0.017]***	[0.020]**	[0.002]	[0.004]
Observations	3555	3555	3555	3555
Mean	-0.015	0.047	0.214	0.548

Notes. * significant at 10%; ** significant at 5%; *** significant at 1%. Administrative data from COMIPEMS. Standard errors clustered at the school-group level. School fixed effects. Control variables used are age, whether the student has special needs, mother's years of education, if the student had no entry exam score, standardized baseline exam score, rank in the class in baseline and proportion of women in the group. *Estimation sample:* All girls that applied to high school.

Table A.4: Effects on Girls' Performance (Figure 6)

	7th grade exam (1)	8th grade exam (2)	9th grade GPA (3)
Share high achieving girls	0.078	-0.029	0.002
	[0.051]	[0.049]	[0.027]
Share high achieving boys	-0.049	-0.048	-0.017
	[0.044]	[0.039]	[0.028]
Share high achieving girls × baseline score	-0.007	-0.040	-0.024
	[0.033]	[0.030]	[0.016]
Share high achieving boys × baseline score	-0.004	-0.059	-0.017
	[0.030]	[0.026]**	[0.015]
Observations	1792	1655	3551
Mean	0.155	0.100	0.381

Notes. Results with sample that sat for the high school entry exam only. Graduation and GPA variables are from CDIAR administrative data. Exam scores are from survey data on a selected sample. Specification is the same as in previous tables. *Estimation sample:* Panels A and B refers to a subsample of girls that applied to high school and took the administered standardized exam in 7th or 8th grade (see Section 2 for details). Panel C refers to all girls that applied to high school.

1 Results for boys

1.1 Descriptive Statistics

Table 1.1: Comparison of the Analysis Sample and the Survey Samples (boys only)

	7th grade sample		Applied to H-S sample		Assigned to H-S sample	
	Observations	Mean	Observations	Mean	Observations	Mean
	(1)	(2)	(3)	(4)	(5)	(6)
Age	4941	11.780	3372	11.735	2772	11.727
Special needs student	4941	0.030	3372	0.024	2772	0.021
Lives with both parents	4751	0.644	3302	0.681	2716	0.688
Years of educ., father	3955	10.027	2843	10.454	2349	10.491
Years of educ., mother	4941	9.238	3372	9.941	2772	10.019
Std. baseline exam, no extemp.	4736	-0.039	3292	0.160	2709	0.242
Std. primary GPA	4776	-0.235	3312	0.025	2724	0.128

Notes. p-value estimated using an OLS estimator at the school-group level, controlling for school fixed effects and robust standard errors. For more information on sample size please go to the Online Appendix Section 2.

Table 1.2: Variation in high-achieving girls and boys

	Share high achieving girls	Share high achieving boys	Number high achieving girls	Number high achieving boys
	(1)	(2)	(3)	(4)
Raw Variables				
Mean	0.19	0.18	3.57	3.70
s.d.	0.16	0.16	3.26	3.33
[Min, Max]	[0.00, 0.76]	[0.00, 0.75]	[0.00, 16.00]	[0.00, 15.00]
Net of school fixed effects				
Mean	0.00	0.00	0.00	0.00
s.d.	0.08	0.08	1.51	1.62
[Min, Max]	[-0.22, 0.21]	[-0.27, 0.27]	[-4.47, 4.56]	[-5.39, 5.94]
Observations	4941	4941	4941	4941

Notes. High achievers defined as being over the 75th percentile of the complete baseline exam distribution for 2015. For more information on sample size please go to the Online Appendix Section 2.

Table 1.3: Balance of Observable Characteristics

Panel A: Background variables	Lives with both parents (1)	Years of education (father) (2)	Years of education (mother) (3)	Household size (4)	
Share high achieving girls	-0.000	0.077	0.017	-0.006	
	[0.013]	[0.095]	[0.102]	[0.043]	
Share high achieving boys	-0.009	-0.150*	-0.180*	0.017	
	[0.012]	[0.083]	[0.101]	[0.041]	
Observations	4751	3955	4941	4751	
Panel B: Individual characteristics	**Age (1)**	**Special needs (2)**	**Repeater (3)**	**Std. Baseline exam (4)**	**Std. Primary GPA (5)**
Share high achieving girls	-0.021	-0.005	-0.000	0.003	0.025
	[0.019]	[0.004]	[0.002]	[0.023]	[0.025]
Share high achieving boys	0.009	-0.001	0.002	-0.020	-0.016
	[0.016]	[0.004]	[0.002]	[0.014]	[0.024]
Observations	4941	4941	4941	4941	4776

Notes. This table is based on separate OLS regressions for each school with age, special needs (dummy), lives with parents (dummy), parent with secondary or more (dummy), standardized score for middle school entry, female, and standardized primary GPA as dependent variables. The explanatory variables are a set of group dummies. For more information on sample size please go to the Online Appendix Section 2.

1.2 Results

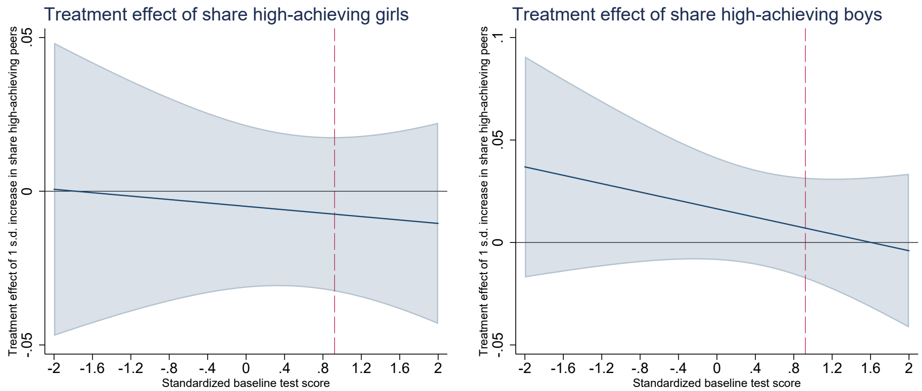
Table 1.4: Selection into high school

	(1)	(2)
Share high achieving girls	0.020	0.020
	[0.011]*	[0.011]*
Share high achieving boys	0.022	0.024
	[0.011]**	[0.011]**
Share high achieving girls × baseline score	-	-0.008
	-	[0.007]
Share high achieving boys × baseline score	-	-0.013
	-	[0.008]*
Observations	4941	4941

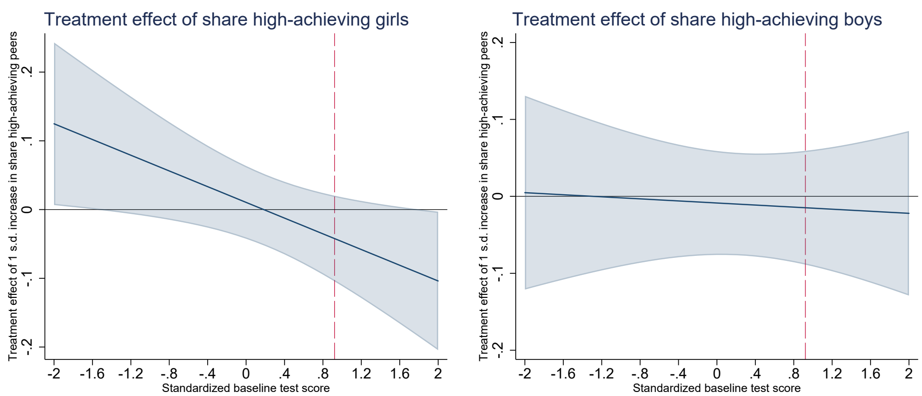
Notes. OLS estimator using student demographic variables as controls, school fixed effects, and clustered at the school-group level standard errors. Registers to high school is defined as one if the student registered to COMIPEMS and presented the high school placement exam. For more information on sample size please go to the Online Appendix Section 2.

Figure 1.1: Marginal Effect on high school admission

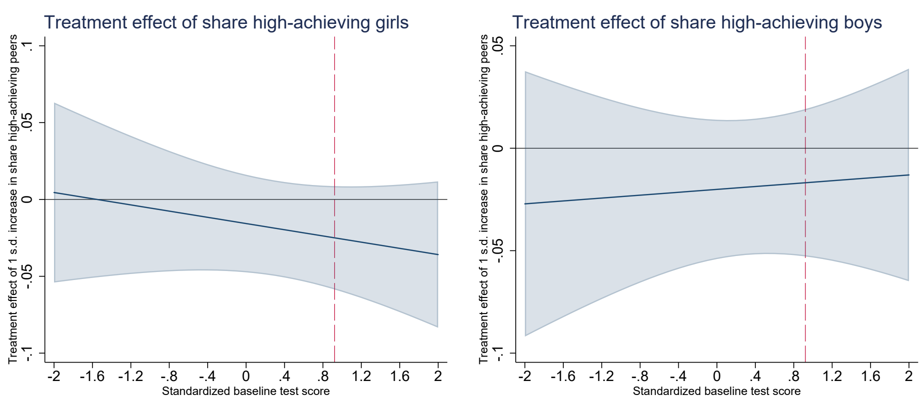
(a) Probability of being assigned to a high school



(b) Assigned high school selectivity

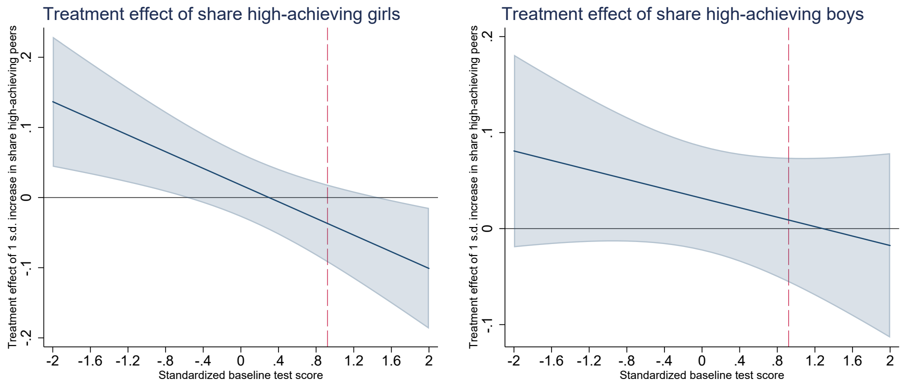


(c) Assigned to academic high school



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

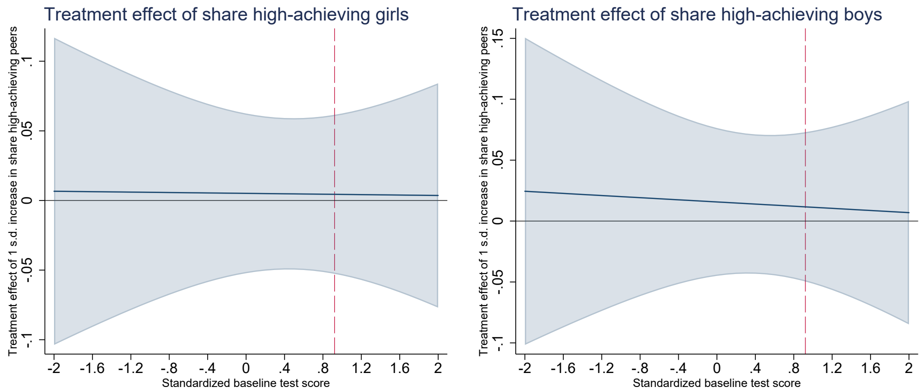
Figure 1.2: Marginal Effect on high school entry exam



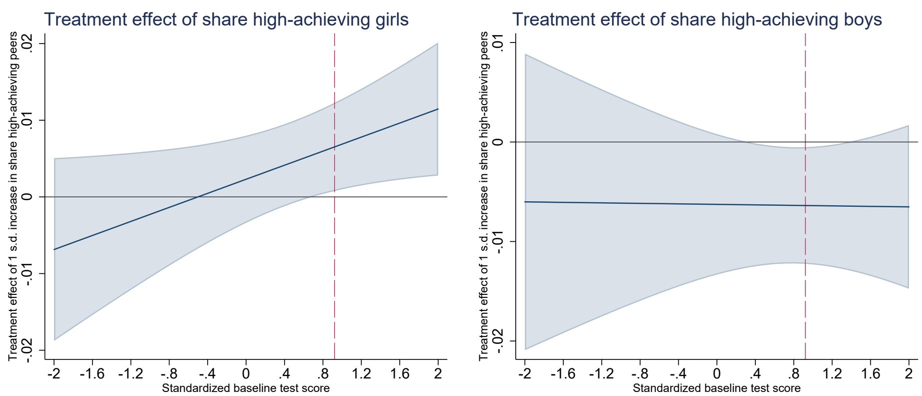
Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 1.3: Marginal Effect on preferences

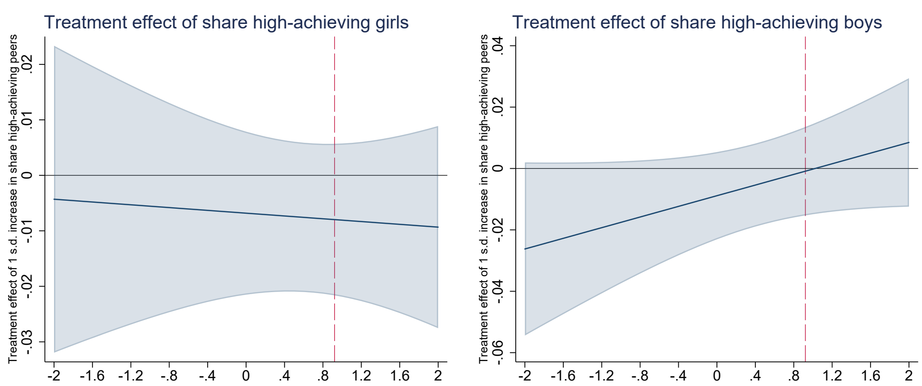
(a) Average school selectivity in portfolio



(b) Heterogeneity of high school selectivity in portfolio



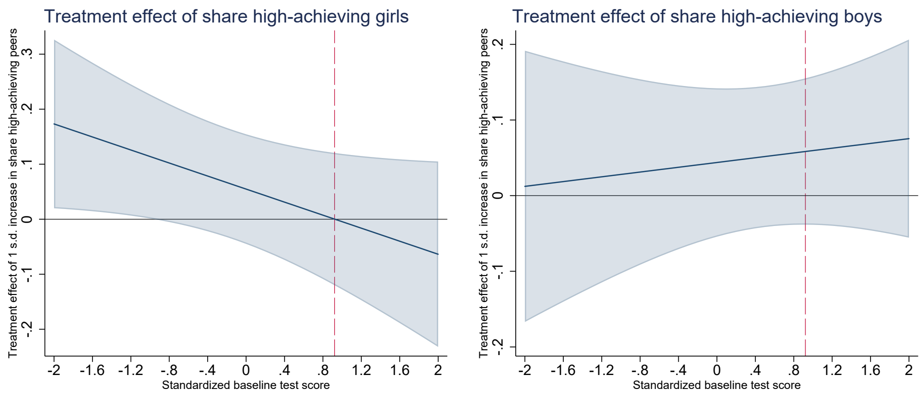
(c) Share of academic high schools in portfolio



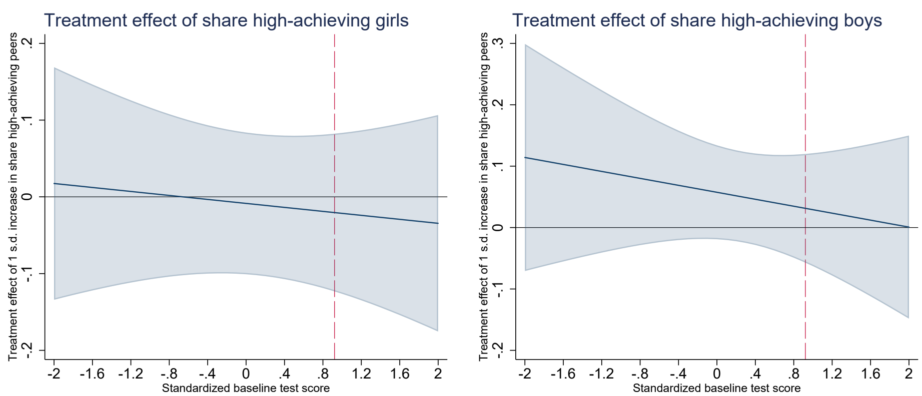
Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 1.4: Marginal Effect on academic achievement: Dynamic effects

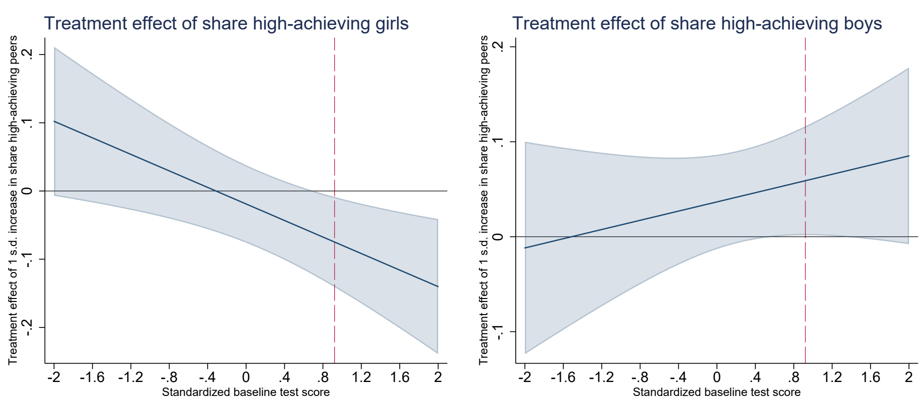
(a) Standardized test scores (Grade 8)



(b) Standardized test scores (Grade 7)



(c) Standardized grade point average (Grade 9)



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

2 Samples description

Table 2.1: Description of Samples

By Gender (9627)				**Total**	
Girls	4686	Boys	4941	All	9627
Girls by High School Application (4686)		**Boys by High School Application (4941)**		**All by High School Application (9627)**	
Take H-S exam	3555	Take H-S exam	3372	Take H-S exam	6927
Do not take exam	1131	Do not take exam	1569	Do not take exam	2700
Girls by High School Admittance (3555)		**Boys by High School Admittance (3372)**		**All by High School Admittance (6927)**	
Admitted 1st round	2906	Admitted 1st round	2772	Admitted 1st round	5678
Not admitted 1st round	649	Not admitted 1st round	600	Not admitted 1st round	1249
Girls who applied to HS and are part of the survey sample		**Boys who applied to HS and are part of the survey sample**		**All who applied to HS and are part of the survey sample**	
7th grade exam	1792	7th grade exam	1678	7th grade exam	3470
8th grade exam	1655	8th grade exam	1546	8th grade exam	3201

Notes. This table reports the number of observations for the several samples used in the paper. The samples change due to decisions made at different moments of time. The data for the 7th grade survey, which was used in the construction for the indexes, varies across indexes due to missing values and are not reported here. Due to extension, we only report the number of students who present the 7th grade exam, which was carried out during the same session of the survey. We also do not report on the 9th grade outcomes given that this is administrative data and should be available for all students who applied to High School; in the case of the 9th grade GPA there are 3551 observations due to missing values on four students.

Table 2.2: Comparison of students across samples

	7th grade sample Observations (1)	Mean (2)	Applied to H-S sample Observations (3)	Mean (4)	Assigned to H-S sample Observations (5)	Mean (6)
Age	4686	11.748	3555	11.722	2906	11.720
Special needs student	4686	0.015	3555	0.007	2906	0.004
Lives with both parents	4527	0.658	3488	0.684	2853	0.688
Father's yrs. of education	3766	9.886	2968	10.180	2431	10.238
Mother's yrs. of education	4686	9.306	3555	9.792	2906	9.892
Std. baseline exam	4509	0.040	3478	0.158	2847	0.243
Std. primary GPA	4562	0.246	3501	0.429	2865	0.531

Notes. This table reports the average and number of observations for the three main samples used in the paper. The samples change due to decisions made at different moments of time. The 7th grade sample consists of all girls who were in school at the beginning of 7th grade. Applied to H-S is the sample of students who took the High-School entry exam (if the report grade of the student is zero, we assume that did student may have registered, but did not take the exam). The assigned to High-School sample consists of students who were assigned to a High-School in the first allocation round. For more information on sample size please go to the Online Appendix Section 2.

Table 2.3: Comparison of High School Exam Takers and Non Takers

Variables of interest:	Does not take admission exam Observations (1)	Mean (2)	Takes the admission exam Observations (3)	Mean (4)	P value of difference (5)
Age	1131	11.83	3555	11.72	0.00
Special needs student	1131	0.04	3555	0.01	0.00
Lives with both parents	1039	0.57	3488	0.68	0.00
Years of educ., father	798	8.79	2968	10.18	0.00
Years of educ., mother	1131	7.78	3555	9.79	0.00
Std. baseline exam, no extemp.	1031	-0.35	3478	0.16	0.00
Std. primary GPA	1061	-0.36	3501	0.43	0.00

Notes. P value estimated using an OLS estimator where we regress each variable of interest against a dummy variable of having presented the High-School entry exam and controlling for school fixed effects. We use robust standard errors. For more information on sample size please go to the Online Appendix Section 2.

3 Main results without baseline score interaction

Table 3.1: Effects on Girls' Placement Outcomes without interaction with baseline score

	Assigned to school (1)	Cut-off assigned school (2)	Assigned to an academic school (3)
Share high achieving girls	-0.003	0.809	-0.021
	[0.012]	[0.616]	[0.018]
Share high achieving boys	-0.015	-0.828	0.001
	[0.011]	[0.559]	[0.016]
Observations	3555	2906	2906
Mean	0.817	61.692	0.461

Notes. * significant at 10%; ** significant at 5%; *** significant at 1%. Administrative data from COMIPEMS. Standard errors clustered at the school-group level. School fixed effects. Control variables used are age, whether the student has special needs, mother's years of education, if the student had no entry exam score, standardized baseline exam score, rank in the class in baseline and proportion of women in the group. For more information on sample size please go to the Online Appendix Section 2.

Table 3.2: Effects on Girls' Entry Exam Score and Preferences without interaction with baseline score

	High-school entry exam (1)	Mean cut-off in prefs. (2)	CV of portfolio cut-offs (3)	Share of academic options in portfolio (4)
Share high achieving girls	0.044	0.019	-0.002	-0.010
	[0.023]*	[0.027]	[0.004]	[0.007]
Share high achieving boys	-0.035	-0.031	0.003	-0.009
	[0.020]*	[0.027]	[0.004]	[0.007]
Observations	3555	3555	3555	3555
Mean	-0.015	0.047	0.214	0.548

Notes. * significant at 10%; ** significant at 5%; *** significant at 1%. Administrative data from COMIPEMS. Standard errors clustered at the school-group level. School fixed effects. Control variables used are age, whether the student has special needs, mother's years of education, if the student had no entry exam score, standardized baseline exam score, rank in the class in baseline and proportion of women in the group. For more information on sample size please go to the Online Appendix Section 2.

Table 3.3: Effects on Girls' Performance without interaction with baseline score

	7th grade exam (1)	8th grade exam (2)	9th grade GPA (3)
Share high achieving girls	0.078	-0.033	-0.002
	[0.051]	[0.049]	[0.026]
Share high achieving boys	-0.050	-0.065	-0.021
	[0.042]	[0.040]	[0.026]
Observations	1792	1655	3551
Mean	0.155	0.100	0.381

Notes. Results with sample that sat for the high school entry exam only. Graduation and GPA variables are from CDIAR administrative data. Exam scores are from survey data on a selected sample. Specification is the same as in previous tables. For more information on sample size please go to the Online Appendix Section 2.

4 Robustness: classroom shares

4.1 Descriptive Statistics

Table 4.1: Variation in high-achieving girls and boys

	(1) Share high achieving girls wrt. all	(2) Share high achieving boys wrt. all	(3) Low achieving girls	(4) Low achieving boys
Raw Variables				
Mean	0.10	0.09	3.84	3.62
s.d.	0.08	0.08	3.42	3.32
[Min, Max]	[0.00, 0.42]	[0.00, 0.36]	[0.00, 16.00]	[0.00, 15.00]
Net of school fixed effects				
Mean	0.00	0.00	0.00	0.00
s.d.	0.04	0.04	1.57	1.63
[Min, Max]	[-0.14, 0.13]	[-0.13, 0.16]	[-5.04, 4.17]	[-4.91, 6.45]
Observations	4686	4686	4686	4686

Notes. High achievers defined as being over the 75th percentile of the complete baseline exam distribution for 2015. For more information on sample size please go to the Online Appendix Section 2.

Table 4.2: Balance of Observable Characteristics

Panel A: Background characteristics					
	Lives with both parents (1)	Years of education (father) (2)	Years of education (mother) (3)	Household size (4)	
Share high achieving girls wrt. all	0.004	-0.066	-0.265***	0.021	
	[0.012]	[0.084]	[0.084]	[0.052]	
Share high achieving boys wrt. all	0.017	-0.032	0.018	-0.049	
	[0.013]	[0.081]	[0.079]	[0.048]	
Observations	4527	3766	4686	4527	
Panel B: Individual characteristics					
	Age (1)	Special needs (2)	Repeater (3)	Std. Baseline exam (4)	Std. Primary GPA (5)
Share high achieving girls wrt. all	-0.002	0.000	0.001	-0.010	-0.016
	[0.017]	[0.003]	[0.001]	[0.017]	[0.021]
Share high achieving boys wrt. all	0.015	0.000	0.001	-0.005	-0.042**
	[0.015]	[0.003]	[0.001]	[0.020]	[0.021]
Observations	4686	4686	4686	4686	4562

Notes. This table is based on separate OLS regressions for each school with age, special needs (dummy), lives with parents (dummy), parent with secondary or more (dummy), standardized score for middle school entry, female, and standardized primary GPA as dependent variables. The explanatory variables are a set of group dummies. For more information on sample size please go to the Online Appendix Section 2.

4.2 Results

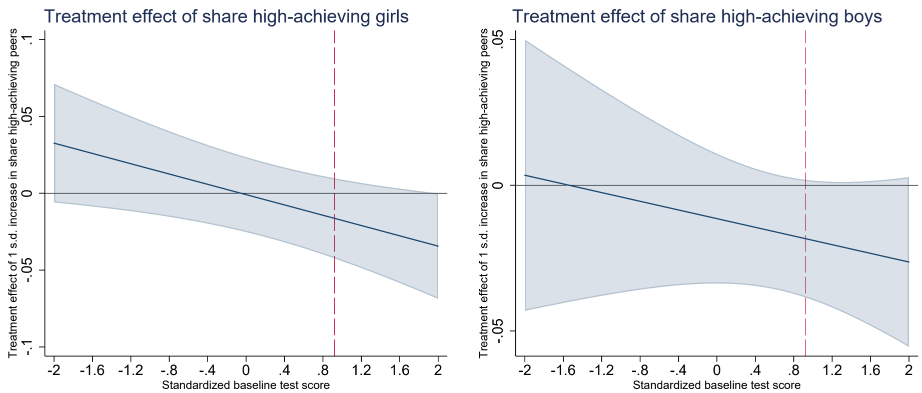
Table 4.3: Selection into high school

	(1)	(2)
Share high achieving girls wrt. all	-0.002	-0.003
	[0.011]	[0.011]
Share high achieving boys wrt. all	0.006	0.009
	[0.011]	[0.012]
Share high achieving girls wrt. all × baseline score		-0.001
		[0.007]
Share high achieving boys wrt. all × baseline score		-0.011
		[0.008]
Observations	4686	4686

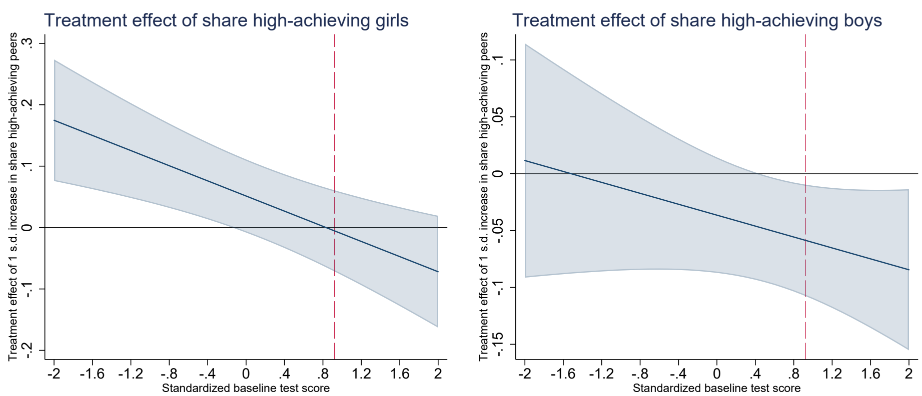
Notes. OLS estimator using student demographic variables as controls, school fixed effects, and clustered at the school-group level standard errors. Registers to high school is defined as one if the student registered to COMIPEMS and presented the high school placement exam. For more information on sample size please go to the Online Appendix Section 2.

Figure 4.1: Marginal Effect on high school admission

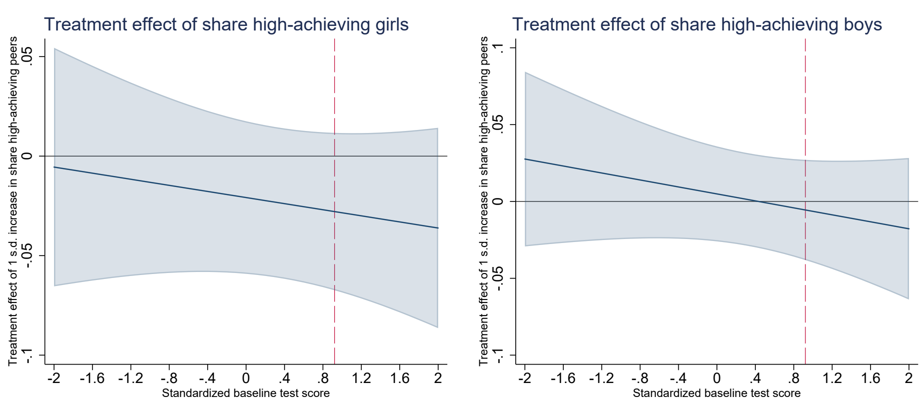
(a) Probability of being assigned to a high school



(b) Assigned high school selectivity

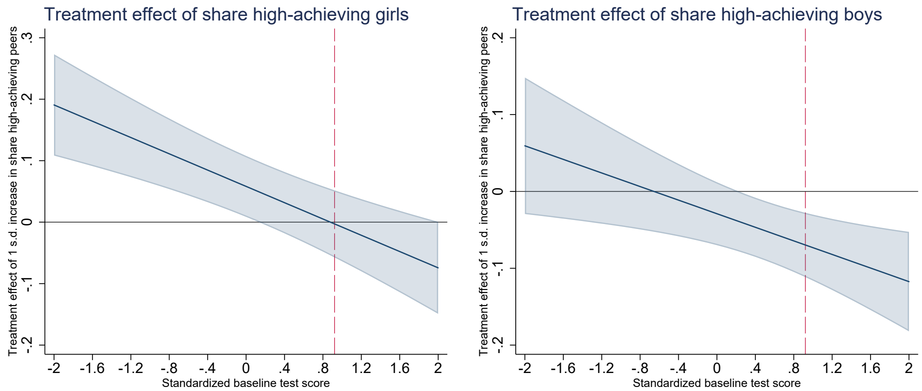


(c) Assigned to an academic high school



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

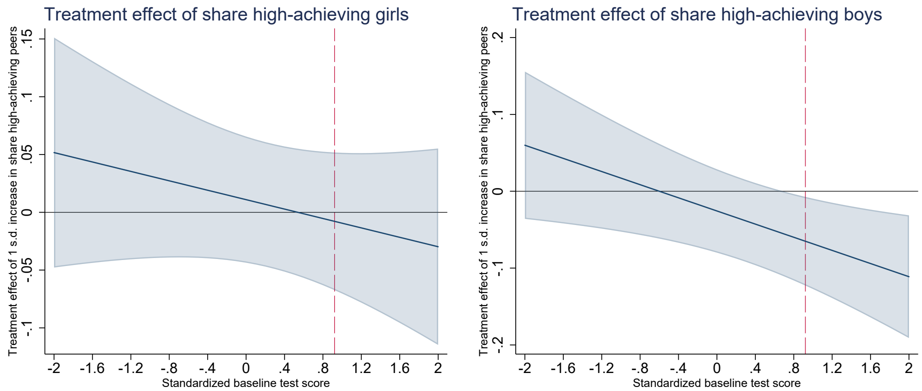
Figure 4.2: Marginal Effect on high school entry exam



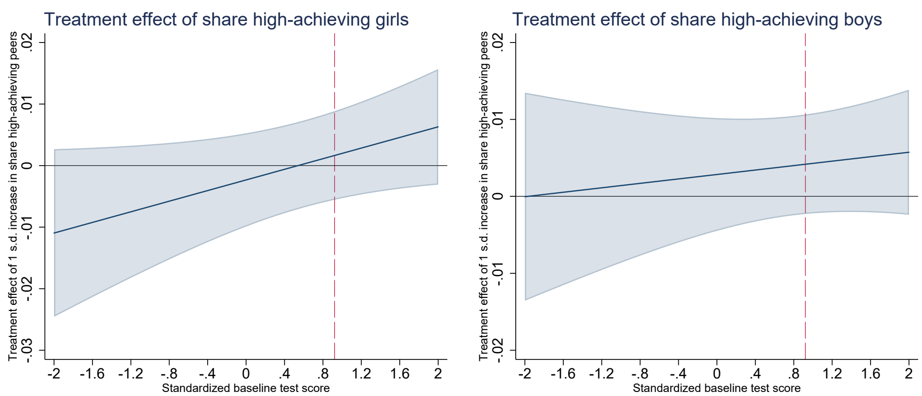
Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 4.3: Marginal Effect on preferences

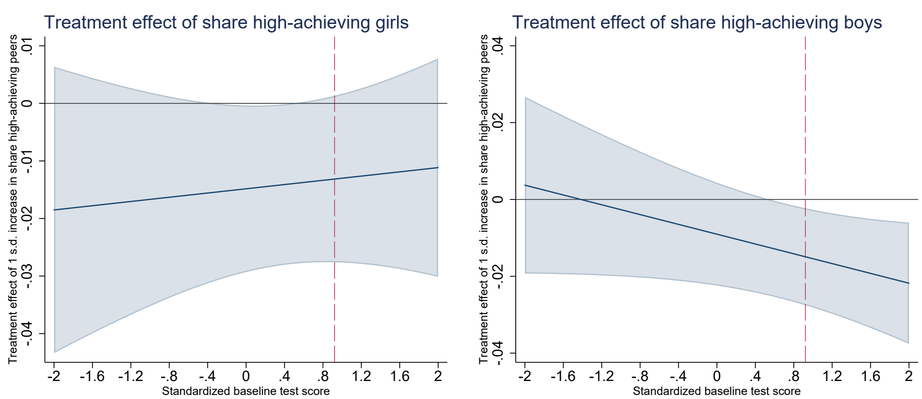
(a) Average school selectivity in portfolio



(b) Heterogeneity of high school selectivity in portfolio



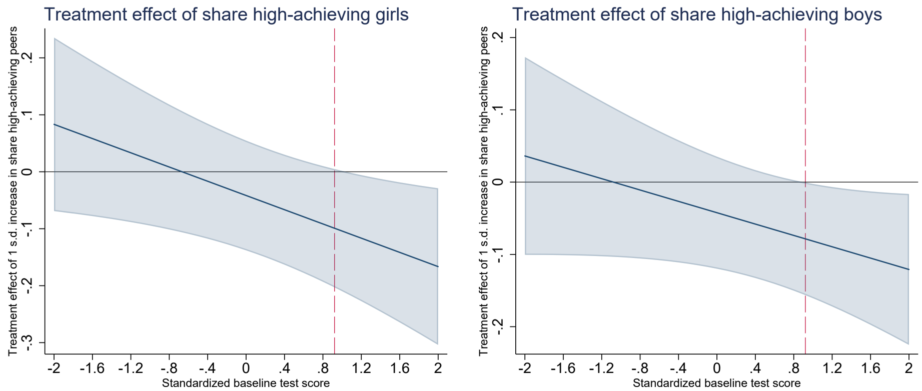
(c) Share of academic high schools in portfolio



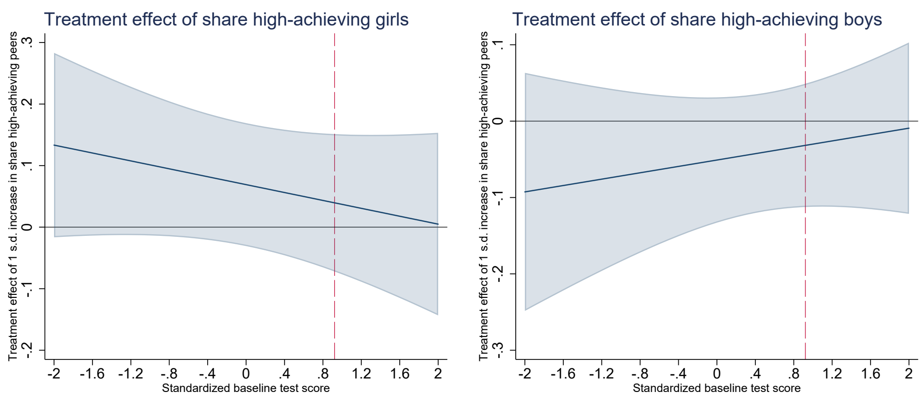
Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 4.4: Marginal Effect on academic achievement: Dynamic effects

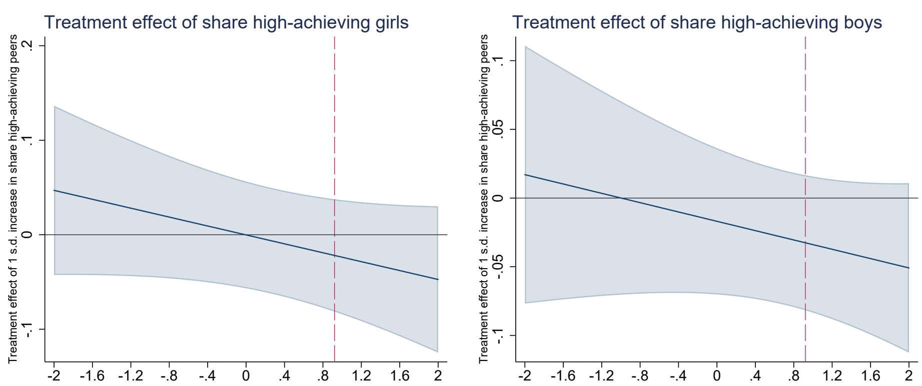
(a) Standardized test scores (Grade 8)



(b) Standardized test scores (Grade 7)



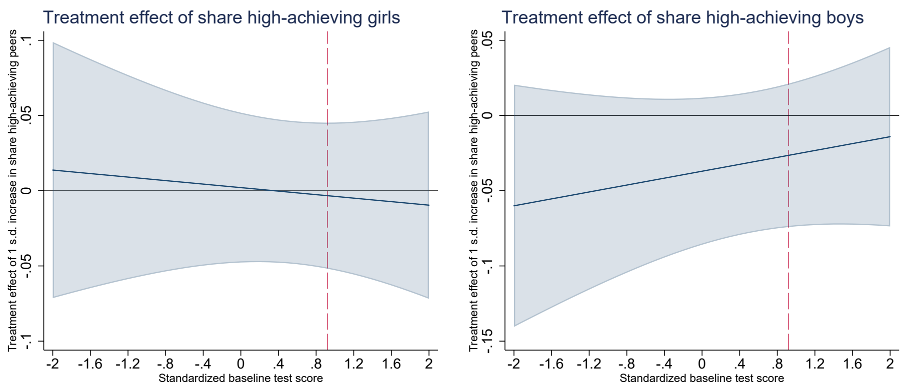
(c) Standardized grade point average (Grade 9)



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

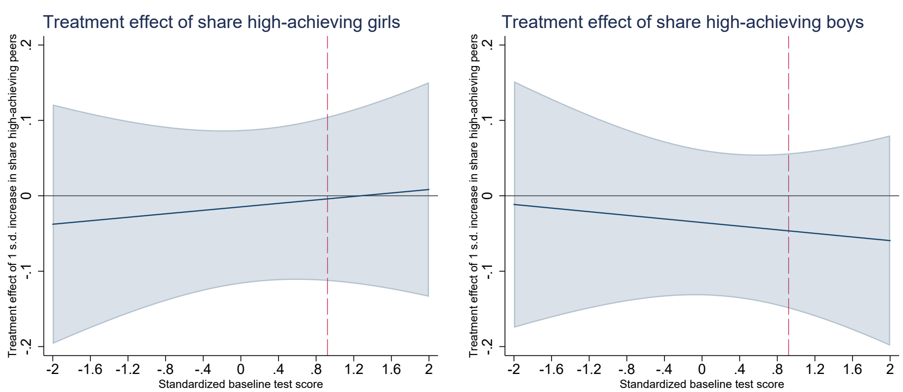
5 Other results

Figure 5.1: Marginal Effect on absences (Grade 7)



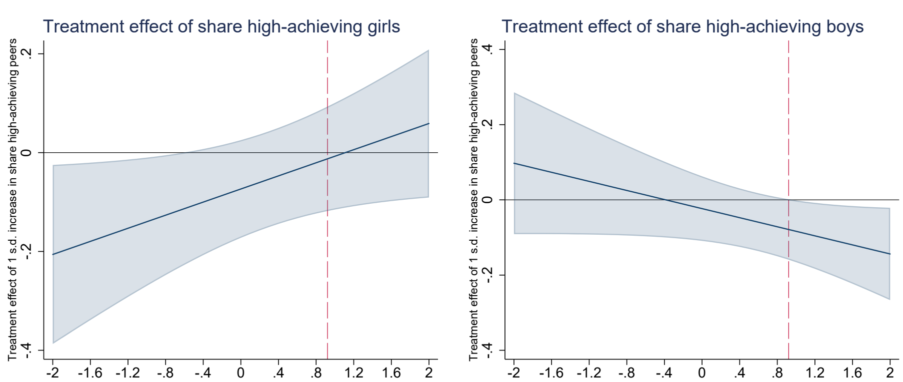
Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 5.2: Marginal Effect on classroom effort



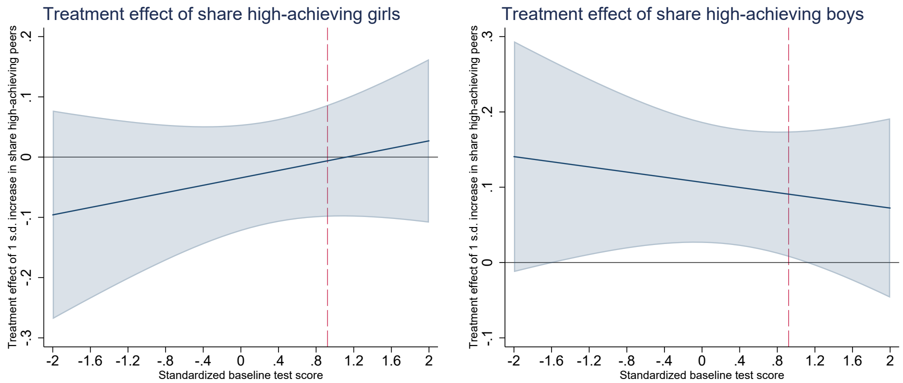
Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 5.3: Marginal Effect on peer support



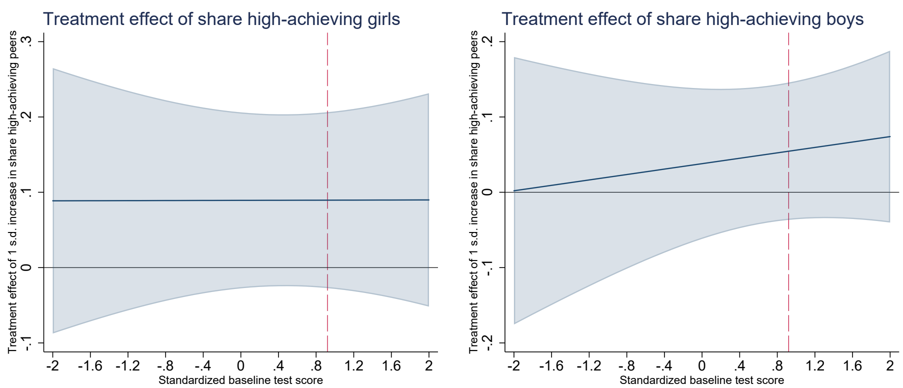
Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 5.4: Marginal Effect on disruptive behavior



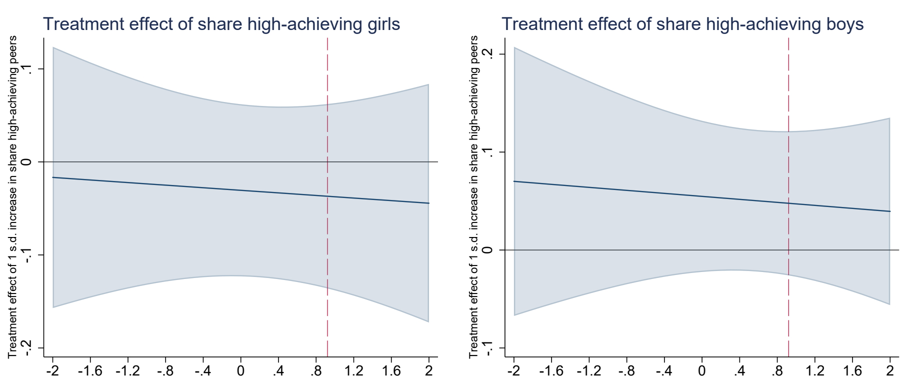
Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 5.5: Marginal Effect on risky behavior



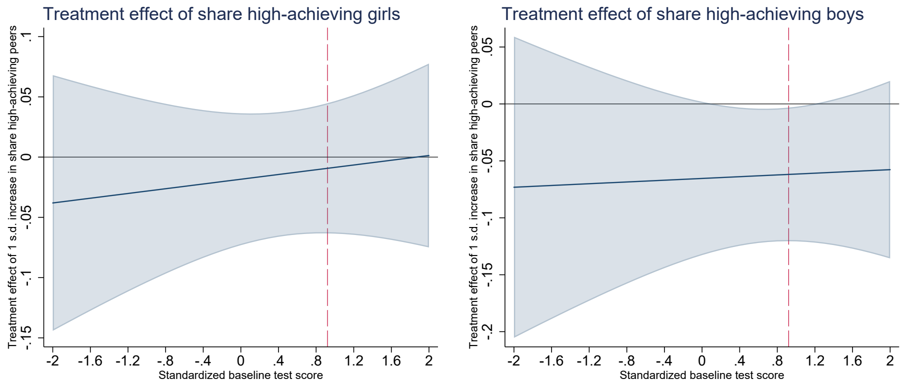
Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 5.6: Marginal Effect on school behavioral problems



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.

Figure 5.7: Marginal Effect on truancy



Notes: This graph plots the marginal effect of the share of high-achieving girls (left) and the share of high-achieving boys (right) on the outcome of interest (y-axis) and the standardized baseline test score (x-axis). This is the derivative of the model shown in equation 1 in the main text with respect to each of the shares. Standard errors calculated using the Delta method.