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DIPARTIMENTO DI ECONOMIA, METODI QUANTITATIVI E STRATEGIA DI IMPRESA

A peer like me? Early exposure to high achievers in math and later educational outcomes*

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Abstract

This paper investigates whether exposure to academically gifted peers of the same and opposite gender in primary school (grade 5, at age 10) affects later academic achievement (grade 8, at age 13) and high-school track choice. For identification we exploit random allocation of kids across classes within primary schools. We document that, conditional on primary school fixed effects and grade 8 class fixed effects, as well as on baseline achievement, a higher share of same/opposite-gender high-achievers in math in primary school is related, both for boys and girls, to better/worse later math academic achievement in grade 8 and to a higher/lower probability of choosing a scientific high-school track. We argue that these results are consistent with a role model channel.

Keywords: Peer effects, early education stage, gender-specific effects
JEL Classification: I21, I24, J24

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1 Introduction

School environment affects educational outcomes, including both academic achievement and students' choices. Peers are one of the most important element of the school environment. They can affect outcomes not just because of student-to-student spillovers, influence on teaching style or group functioning (Sacerdote, 2011), but also through psychological mechanisms that act on students' effort and on motivation, such as pressure, aspirations, or social norms that may arise and change as a result of the exposure to peers. For instance, role models have the potential to influence individual behavior and school performance. Their effect is based on the concept that "seeing is believing". Students are often uncertain about their academic ability (Zafar, 2011; Stinebrickner and Stinebrickner, 2012), in particular at early stages; therefore, observing classmates with similar/opposite characteristics – for instance same/opposite gender – doing particularly well may affect the kids' perception about their own academic ability and, as a consequence, may affect their decision on how much time and effort to devote to academic activities, with potentially long-lasting effects.[1]

This paper investigates this issue, looking at whether exposure to high achievers of the same and opposite gender in the early stage of the educational process affects later academic outcomes and school choices. In particular, we ask (*i*) whether exposure to high achievers differs depending on own and high-achievers gender, (*ii*) whether its effect is long lasting, and (*iii*) whether we can ascribe it to a role model mechanism. To do so, we examine the effect of exposure to high achievers in math in the last year of primary school (grade 5, at age 10) on both math achievement in the last year of the middle school (grade 8, at age 13) and on the probability to choose a scientific high-school track. We focus on math-related outcomes in view of the well-documented gender gap in math achievement and in the investment in STEM-specific human capital that, in turn, lead to subsequent occupational segregation and gender gap in earnings (Black et. al, 2008; OECD, 2018).

We investigate this issue within the Italian school setting by using administrative data provided by the National Institute for the Evaluation of the Education System (INVALSI) for the universe of the cohort of Italian students enrolled in their fifth year of primary school (grade 5) in the 2012-13 school year, that we are able to follow across grade 8 (last year of middle school) and grade 10 (second year of high school). The data contain information on math achievement in standardized tests administered by INVALSI itself, in addition to information on teachers' subject-specific assessment and on socio-demographic characteristics, which are drawn from school administrative records. Furthermore,

[1]There is ample evidence showing that peer effects differ depending on peers' gender (Hoxby, 2002; Lavy and Schlosser, 2011; Schneeweis and Zweimüller, 2012; Brenøe and Zölitz, 2020; Zölitz and Feld, 2021) and depending on whether peers are of own or different gender (Anelli and Peri, 2017; Cools et at., 2021; Mouganie and Wang, 2020; Feld and Zölitz, 2021).

in grade 5 and 10 students have to fill in a questionnaire that we use to gather information about students and their parental background, in addition to several other information on students' learning strategies, attitudes, motivation and engagement in school subjects.

This very rich data source allows us to compute gender-specific class-level shares of high-achievers in math in the last year of primary school (grade 5) that we relate to later outcomes. For identification, we exploit within-grade 8 class variation in the exposure to the gender-specific shares of high achievers in primary school, holding fixed both individual and grade 5 class-level characteristics. In other words, we compare students with the same baseline characteristics – including academic achievement – in the same grade 8 class, who attended the same primary school in different classes, and were therefore exposed to different gender-specific shares of high achievers.[2]

A unique characteristic of our study, in fact, is that we observe the class identifier at each school stage. This feature of our data allows us to exploit the within primary school variation in class composition and then to compare students across classes of a given primary school and grade, rather than across cohorts, as it is usually done in this literature. Our identifying assumption is that, conditional on attending a given primary school and a given middle school class, and conditional on the baseline achievement in grade 5 and on teacher quality, the share of gender-specific high achievers in the primary school class is as good as random. To provide evidence in support of our identifying assumption, we test the independence of the gender-specific shares of high-achievers from students' observable characteristics and show that observables are indeed balanced across classes (within primary schools).

The first key finding of our empirical analysis is that, for both girls and boys, exposure to a higher share of same-gender high-achievers in grade 5 is positively related to later academic achievement in grade 8. The second finding is that both boys and girls' academic achievement is negatively affected by the presence of high-achievers of the opposite gender. The magnitude of the effect is not negligible. The combination of the two mechanisms implies that relocating a girl from a class with a high share of high achieving boys (e.g. at the 90^{th} percentile) and a low share of high achieving girls (e.g. one standard deviation below the mean) to a symmetric class with a low share of high achieving boys (e.g. at the 10^{th} percentile) and a substantial share of high achieving girls (e.g. one standard deviation above the mean) raises her 8^{th} grade math score from 10 percentage points below the male average to 10 percentage points above it.

Interestingly, these results hold also on the sub-sample of students who have no grade 5 high-

[2]In other words, our baseline specification includes both primary school fixed effects and grade 8 class fixed effects, plus grade 5 class controls and individual controls.

achievers in their grade 8 class, albeit the effect is sometimes smaller in magnitude (but still everywhere statistically significant). This implies that our results are not (fully) ascribable to the exposure to the grade 5 high achievers also in the subsequent school stage, and begs the question of what is the underlying mechanism.

We can think of two different channels that may potentially explain the positive effect of being exposed to a high share of same-gender high-achievers in grade 5 on academic achievement in grade 8 (over and above the academic achievement in grade 5, which is controlled for). The first is a long-lasting peer effect: kids exposed to same-gender high-achievers in grade 5 acquire the skills needed to improve their academic performance *permanently*, e.g. they learn the "right" study method. For this reason they do well also in grade 8. This channel, however, barely explains the negative effect of being exposed to a high share of opposite-gender high-achievers in grade 5. It is, in fact, hard to think that female/male kids *unlearn* how to study effectively if exposed to high share of opposite-gender high-achievers in grade 5.

The second channel is related to gender-specific role models, and has, instead, the potential to explain both the positive and negative effects. Seeing same-/opposite-gender classmates doing particularly well in a specific subject in early educational stages may contribute shaping, both positively and negatively, kids' beliefs about gender-specific academic ability, or, more specifically in our context, about gender-specific aptitude and predisposition towards that specific subject. As mentioned above, this awareness may permanently affect kids' decisions on how much time and effort to devote to academic activities, with potentially enduring effects.

While we cannot exclude that the long lasting peer effect channel described above is at work in generating the positive effect of being exposed to a high share of same-gender high-achievers, the fact that the negative effect of opposite-gender high-achievers is likely explained by a role model mechanism, induces us to believe that such a channel has the potential to (partly) explain also the positive effect of same-gender high-achievers.

Turning to the high-school track choice we find, in line with the previous results, that the probability of choosing the academic high school track that is more intensive in math and science (which usually conducts to college degrees in STEM disciplines), is positively/negatively related to the share of same-/opposite-gender high-achievers. Again, these results hold also on the sub-sample of students who have no grade 5 high-achievers in their grade 8 class, with the notable exception of the effect of high-achieving girls on girls which turns to (a precisely estimated) zero. This shows that, as far as girls are concerned, the positive effect of being exposed to a high share of high-achieving girls in grade 5 is not enough to induce them to choose the math-intensive high school track, unless girls keep being exposed to at least one grade 5 high-achieving girl also during middle school.

Finally, exploiting the richness of our data, we find evidence that exposure to high-achievers in grade 5 is related to later attitudes and disposition towards math, suggesting that the effect we find possibly operates also through psychological mechanisms.

With this study, we contribute to a recent growing literature on the effect of high achieving peers on educational outcomes. Mouganie and Wang (2020) study the effect of exposure to gender-specific high-achievers in math in the first year of high school on subsequent high school track choice and on college outcomes using administrative data from a large metropolitan area in Southern China. Similar to us, they find that exposure to high-achieving girls increases the likelihood that girls choose a STEM track. Cools, Fernandez and Patacchini (2021) explore how exposure in high school to "high flyers" (i.e. students with highly-educated parents) of both genders affects later academic outcomes using US longitudinal survey data. They find asymmetric gender effects, with a negative effect of exposure to male high flyers on girls later educational and labor market outcomes and no effect of exposure to female high flyers. They find no effects of high flyers of both genders on boys. Feld and Zölitz (2021) focus on a much later educational stage, i.e. on Dutch university students; exploiting random assignment of students to sections, they investigate how the achievement of peers of both genders affects course and major choices and labor market outcomes. They find that having higher-achieving peers has no effects on educational choices.

Our paper adds to this literature by looking at the effect of exposure to high achieving peers in an *early* stage of the educational process, namely during primary school, on *later* outcomes, which helps us pinning down the role model channel separately from a standard peer effect channel. Both economic and psychological literature has shown that peer influence is already in place in the primary school years on a range of outcomes, including academic engagement and achievement (Hoxby, 2000; Ammermueller and Pischke, 2009; Lavy and Schlosser, 2011; Gremmen et al., 2018; Lease et al., 2020). Understanding the effect of early exposure to math high achievers can help set students on a path toward the development of positive attitudes toward math, and to prevent or reduce math anxiety.

The remainder of this paper proceeds as follows: Section 2 provides background on the Italian education system and describes the data, outcomes, and variables of interest. Section 3 describes the estimation strategy. Section 4 presents our finding. Section 5 reports robustness checks. Section 6 presents additional evidence useful for investigating some possible mechanisms behind our results.

Section 7 concludes with some final remarks.

2 The Italian educational setting, data and main variables

2.1 Education in Italy

Education in Italy starts at 6 years of age and is compulsory until 16. The education system is divided into different stages based upon age: primary education (5 grades, starting the year pupils turn 6), middle education (3 grades), and secondary education (5 grades). When moving on from one stage to the next, students change schools and are reshuffled; then, they have totally new teachers and almost all new classmates.

The main criterion for allocating students to a specific school in the first two stages (i.e. primary and middle school) is proximity to their place of residence. Students are eligible to attend a specific school if they live in the school catchment area. Once admitted to a school, students are assigned to a specific class (*sezione*), generally identified by a letter, where the same group of students expect to be together for the entire duration of the stage and where the set of teachers does not generally vary.[3] Importantly, classes are formed by the school staff (generally the school manager aided by a team of teachers), and this process does not take into consideration family preferences for specific teachers or classmates. Until middle school, the educational curriculum is the same for all pupils, and the subjects studied are the same.

At the end of middle school, pupils have to pass a final exam (*Esame di stato*) and move on to high school, where there are three main tracks: *liceo*, technical and vocational. The *liceo* track is specifically designed to prepare students for tertiary education, and the education provided is advanced and mainly theoretical. There are different *liceo* subtracks: scientific, which focusses on scientific subjects (math and science), classical, which focusses on humanities (Italian language, latin and ancient greek), arts, foreign languages and social sciences. The technical track gives students the opportunity to continue either with an occupation or with additional education; it provides both a theoretical education and a specialization that depends on the subtrack. The vocational track prepares students for an occupation upon graduation; it offers education oriented towards practical subjects, and each subtrack focuses on a specific subject in either the services or industry/craft sector (e.g., catering and hospitality or industrial and craft production). Within tracks and subtracks, the pool of subjects is established centrally by the Ministry of Education, and it is the same throughout

[3] This is not true when students change school, for instance because their family moves to a different area, or when teachers are assigned to a different school (this may happen for teachers in their first years of teaching if they have not been definitively assigned to a specific school) or when they retire.

the country (Comi et al., 2017). Students' enrollment in high school tracks is not selective, i.e. any track is accessible from any middle school, and is based on family choice.[4] Any track permits access to university. Within the high school tracks, parental background and learning levels are quite homogeneous, but on average they are higher in the *liceo* track and lower in the vocational track (Schizzerotto and Barone, 2006).

After choosing the track and subtrack, families choose a school among those available. The school choice depends on different factors, such as the school standing or geographical proximity to the place of residence. Also in high school, students are assigned to a specific class (*sezione*) in their first year without taking into account family's or students' preferences, and the classmates will remain the same throughout the stage. Because there are no electives in Italian schools, class interactions are very strong: classmates take the same courses and spend the entire school day together (this happens also in the first two stages).

2.2 Data and sample selection

Since the 2009-10 school year, the Italian National Institute for the Evaluation of the Education System (INVALSI) has conducted yearly evaluations of the entire student population in grades 2, 5, 8 and 10 based on standardized tests.[5] Our empirical analysis uses administrative-level data provided by INVALSI for the universe of the cohort of Italian students enrolled in their fifth year of primary school (grade 5) in the 2012-13 school year. Starting in the 2012-13 school year, INVALSI makes it possible to link students' data across grades through an encoded student number (to ensure anonymity). We are then able to follow our students from grade 5 across grade 8 (last year of middle school) and grade 10 (second year of high school).

The data contain information on the subject-specific scores obtained by students in the national standardized tests administered by INVALSI itself, in addition to information on grades given by teachers in the main subjects and on some students' socio-demographic characteristics including gender, age, citizenship and parents' education and occupation which are drawn from school administrative records. Furthermore, after completion of the tests, in grade 5 and 10 students have to fill in a questionnaire that we are able to merge with the administrative data set thanks to the student identifier. The questionnaire is based on students' self-reports and it is used to gather information about students and their parental background, in addition to several other information on students' learning strategies, attitudes, motivation and engagement in school subjects.

[4]High schools experiencing excess demand are allowed to screen students and do so according to self-defined criteria.
[5]The subjects tested are math, Italian language and, starting from the school year 2017-18, English language. From the school year 2018-19, grade 13 students (last year of high school) are assessed as well.

We first merge the grade 5 and 8 administrative datasets with the questionnaire, and obtain a sample of 439,392 student observations. We drop observations with missing information on the variables we use in the empirical analysis. We further drop the few individuals whose gender is recorded with noise (i.e., it is different in different grades). We exclude classes where more than 30% of students have missing information on gender to reduce noise in measuring the gender-specific shares of high achievers, and classes in primary schools with a single class, as they do not provide between-classes within-school variation in the shares of high achievers. We also drop classes where more than 30% of students have missing information on the 5^{th} grade INVALSI math score due to absence from school on the day the test was administered because this may be correlated with a specific cheating strategy undertaken by teachers that advice low achieving students not to go to school on the day of the INVALSI test. Our final sample includes students in classes between 10 and 27 and consists of 351,277 students in 22,839 classes of 5,513 primary schools and 24,990 classes of 5,498 middle schools. We conduct robustness tests including in the sample classes of all sizes in Section 5. To investigate high school track choice, we further merge the previous dataset to the grade 10 administrative dataset (and questionnaire), and obtain a sample of 289,960 students in 24,937 classes of 3,652 high schools.

2.3 Outcome variables

We focus on two main outcomes: grade 8 math achievement and high school track choice. We use INVALSI scores to measure academic achievement. INVALSI standardized tests, which are administered at the end of the school year, measure not only students' knowledge, but also a large set of skills that students should acquire at school over time, including how they use the acquired knowledge to deal with applied problems. The INVALSI tests may contain multiple choice and open questions, from which a comprehensive score is computed, as in the Program for International Student Assessment (PISA) and in the Trends in International Mathematics and Science Study assessment (TIMSS). Information on individual performance are not returned to students that, then, are not aware of their scores.

The second outcome analyzed in this study is high school track choice. In Italy high school track is chosen in the month of January of grade 8, the last year of middle school. As mentioned in Section 2.1, socio-economic backgrounds and learning levels tend to be different from the other tracks along a hierarchy, with *liceo* at the top and vocational courses at the bottom. Moreover, within the *liceo* track there are different subtracks, offering a specialization in a specific field of study. We study the effect of the share of high-achieving peers in math on the probability to choose the scientific *liceo* subtrack that, beyond attracting higher-achieving students and featuring a more competitive environment compared to both technical and vocational tracks, is particularly focused on scientific subjects (math and science). Notably, around 70% of university students graduating from the scientific *liceo* choose a STEM or economics/business university course of study, a percentage much higher than other *liceo* subtracks and both technical and vocational tracks (MIUR, 2017).

2.4 Variables of interest: defining high achievers

Our variables of interest are the gender-specific shares of high-achievers in the last year of primary school (grade 5). Because the class composition hardly changes during primary school, grade 5 shares proxies quite well such shares during the whole duration of primary school, that covers the first 5 years of compulsory education.[6]

We define high achieving a student who gets a particularly high mark in math. In Italy, the school year is divided in two terms, the first generally ending in January and the second at the end of the school year in June. At the end of each term, students receive a written assessment of their subject-specific achievements. Specifically, they receive a report card that lists, for each subject, the average mark given by teachers in all tests taken during the term. A 10-point scale is used, 6 being the minimum mark for passing. In our data, we observe the first term report card marks. We define high achievers as students who got at least 9 in math on the report card. For each class, we then compute the total number of high achieving girls and boys. Finally, we compute the girls/boys leave-one-out class shares of high achievers for student i as the ratio of high-achieving girls/boys over the total number of girls/boys in the class excluding student i. In the robustness section we test the robustness of our results to a different definition of high achiever.

An important point to stress is that in the Italian school systems students are well aware both of their own report card marks and of the marks of their classmates, because tipically marks are announced publicly by teachers during classes when school assignments are returned back to students.

2.5 Descriptives

Table 1 presents descriptive statistics for our data by gender, including outcomes and the variables of interest. From the table, we see that in both grade 5 and 8 boys outperform girls in math by, respectively, around 4.2% and 5.9%. The share of boys attending the scientific academic track is

[6]Obviously, the class composition in terms of high achievers may change during primary school also if class pupils do not change due to differential pupils' achievement development.

32%, considerably higher than the corresponding share for girls (22.6%). On average around 20 percent of girls and boys in the 5^{th} grade class are high achievers.[7] and slightly less than one half have at least one primary school high achieving classmate in the same middle school class. There is a similar share of migrants among boys and girls. As regards family background, in our empirical analysis we measure it by using ESCS, a standardized variable provided by INVALSI that considers family economic, social and cultural status, as in OECD Pisa. It is created on the basis of three variables, namely parental education and occupation and availability of home resources favouring learning.[8] Table 1 indicates that there are not substantial differences by gender along the three previous dimensions. The vast majority of students (96.6%) are regularly enrolled (i.e., they started primary school in the year of their sixth birthday).

Figure 1 presents descriptive evidence on how girls' and boys' achievement varies by decile of the distribution of the leave-one-out class-level shares of high-achievers of own and opposite gender. In detail, we divide both grade 5 girls' and boys' high-achievers share distribution into deciles and relate them to the average gender-specific math achievement in grade 8. In panel a (b) we plot the deciles of the high-achieving girls (boys) share distribution. Overall, there is a positive relationship between the share of own-gender high-achievers for both girls and boys, while no clear pattern is observed as regards the opposite-gender high-achievers share. Moving from the first to the last decile of the class share of high-performing girls (boys) we observe an increase in girls' (boys') achievement of respectively, 40% and 44% of its standard deviation. Similarly, Figure 2 looks at the relationship between the gender-specific class-level shares of high-achievers of both genders and the probability to choose the scientific academic high school (scientific *liceo*). We observe a similar pattern, namely, a positive relationship between the probability to enroll in a scientific track high school and the share of own gender high achievers for both boys and girl, although in this case the relationship is less clear-cut for girls.

3 Empirical framework

3.1 Identification strategy

Our main objective is to examine how exposure to high-achieving classmates of own and different gender in primary school (grade 5) affect later middle school (grade 8) math achievement and high

[7]Around one quarter of the students belong to grade 5 classes with either no female or male high achiever and only 10% of students have neither a high achieving boy nor a high achieving girl in their class.

[8]The items considered are: a quiet place to study, a desk, a pc, an encyclopaedia, an internet connection and an own bedroom. The figures in Table 1 refer to the average number of items available.

school track choice. Obviously, the simple association between the shares of gender-specific high-achievers and outcomes does not imply a causal relationship because there may be variables or common shocks affecting both high-achievers' shares and outcomes, so that they correlate. In an ideal setting, the causal effect of the shares of gender-specific high-achievers would be estimated by randomly allocating students to different primary and middle school classes. In this case, two identical students would have different exposure to high-achievers only because their classes differ in terms of gender-specific ability composition.

There are several threats to the identification of a causal effect. The first is related to students sorting in primary school classes leading to systematic differences in the distribution of students' ability and achievement between classes. In the Italian institutional context, endogenous sorting of students does happen but mainly at the school level. Thus, at this level the assumption of random assignment is difficult to defend. In detail, the main criterion for assigning students to a specific school is its nearness to the place of residence: each school has a catchment area and students who reside in that area have the right to enroll in the school. Families may also choose a school outside the catchment area if seats are available. Hence, observed and unobserved school factors, such as its location or quality and prestige, may imply a selection process that could bias our estimates of the shares' effect. To address this issue, we include in our model primary school fixed effects.

Once families have chosen a specific primary school, the Italian law prescribes that students are assigned to classes regardless of families' or students' preferences for specific teachers or schoolmates (see Section 2.1). When entering primary school at 6 years of age, schools do not have any information about pupils' ability. The school staff in general tends to form classes as heterogeneously as possible in terms of gender, immigrant status (as also prescribed by the law) and age (born in the first and second semester of the year) composition. Ability, being unobservable, is not taken into account. Apart from respecting such criteria, usually pupils are randomly assigned to classes within a given primary school. In view of this, sorting into classes within primary schools is a much less serious concern in our context. We provide evidence of random assignment within school classes in Section 3.3.

A second important threat to identification is related to teacher quality. Since we measure the share of high achievers in the last year of primary school, even in the absence of students' sorting into primary school classes, it is still possible that such shares are influenced by specific teachers' characteristics that affect later students' outcome as well. For instance, a very good primary school math teacher may lead to a high share of high achievers of both genders and, at the same time, to better subsequent math achievement and to higher probability of choosing a math oriented high school track. Another point to consider is that unobservable teachers' characteristics may have gender-specific effects. For instance, some primary school teachers may have teaching practices that are particularly effective with students of a given gender: this may lead to a higher share of high achievers of that gender and, at the same time, better academic performances of the students of that gender in middle school or a specific high-school track choice. The opposite may happen in case of teachers with stereotypes that penalize a specific gender (Carlana, 2019).

To address these crucial points, we include in our specification the class-level gender-specific (leave-one-out) average achievement computed using the grade 5 math INVALSI score and the individual-level student's achievement math INVALSI score in grade 5. Thus, we control for both the individual and the (rest of the) class math academic achievement in grade 5. These controls should absorb all the teachers' characteristics that might confound the relationship between our variables of interest and subsequent outcomes, including (unobservable) teacher quality. This is key to our identification strategy, as we want to compare students who have the same prior achievement and who differ only in their exposure to high-achievers of different gender during primary school. Our baseline specification will also include a full set of observable class characteristics that could be correlated with the shares of high achievers as well as with the subsequent outcomes of interest.

Finally, it is possible that students with given shares of gender specific high-achievers in primary school self-select into certain middle schools or classes with characteristics that affect grade 8 achievement and high-school track choice. To address this issue, we include in our specification grade 8 class fixed effects. Given that the class identifier is unique in our data, once we control for class fixed effects, we also implicitly control for middle school fixed effects.

To sum up, to identify a causal effect of early exposure to gender-specific high achievers, we exploit idiosyncratic variation in grade 5 class composition in terms of students' achievement by gender within primary schools and within grade 8 classes. In other words, we compare students in a given grade 8 class who have the same baseline achievement, average class characteristics and primary school but have been exposed to a different gender-specific share of high achievers due to differences in the gender-specific achievement composition across classes of a given primary school. We argue that, conditional on attending a given primary school and a given middle school class and conditional on baseline ability and on average primary school class characteristics, the grade 5 class achievement composition by gender is as good as random. Notably, the richness of the data, that contain information on the primary school class identifier, allows us to exploit the within primary school variation in class composition and then to compare students of a given cohort (belonging to the same middle school class) across different primary school classes rather than across cohorts, as it is usually done in the literature.

3.2 Empirical specification

The identification strategy above described is implemented empirically by estimating the following model for academic achievement:

$$\begin{aligned} Y_{i,p,pc,mc} &= \beta_1 GS_{i,p,pc,mc} + \beta_2 BS_{i,p,pc,mc} + \beta_3 GS_{i,p,pc,mc} \times girl_{i,p,pc,mc} + \beta_4 BS_{i,p,pc,mc} \times girl_{i,p,pc,mc} + \\ &\quad \gamma_3 X_i + \delta Z_{pc} + \lambda_p + \eta_{mc} + \varepsilon_{i,p,pc,mc} \end{aligned} \tag{1}$$

The dependent variables are grade 8 INVALSI math attainment and high-school track choice (a dummy equal to one if the individual chooses an academic scientific oriented high school track) of student i who attended primary school p in primary school class pc and who belongs to middle school class mc. The regressors of interest are $GS_{i,p,pc,mc}$ and $BS_{i,p,pc,mc}$, the class shares of high-achieving girls and boys in grade 5 of primary school, and their interactions with the girl dummy.

The coefficients of interest are β_1, β_2, β_3 and β_4 that denote the effect of the share of high-achieving girls on boys (β_1) and girls ($\beta_1 + \beta_3$) and the effect of high-achieving boys on boys (β_2) and girls ($\beta_2 + \beta_4$). We control for a set of individual-specific characteristics (X_i) including gender, citizenship, parental background, individual gender-specific rank within the class and grade 5 INVALSI math attainment. Family background is controlled for by ESCS, a standardized variable provided by INVALSI that measures students' economic, social and cultural status, as in OECD Pisa, and considers parental education, occupation, and home resources.

Next, the matrix Z_{pc} is a vector of grade 5 class characteristics, which includes share of girls, share of migrants, average background, class size and average math achievement by gender. The term λ_p represents primary school fixed effects while the term η_{mc} represents grade 8 class fixed effects. In all estimates, we cluster standard errors both at the primary school level, to allow for the outcomes of pupils attending the same primary school to be correlated, and at the middle school class level, to allow correlation also at that level.

3.3 Evidence in support of the identification strategy

Our identification strategy relies on the assumption that there are no systematic differences in the primary school gender-specific share of high achieving classmates for two girls (or two boys) who are middle school classmates, have the same baseline ability and comes from similar classes of the same primary school. The first condition that has to be met for identification is that there is sufficient variation in the primary school class gender-specific achievement composition. The raw standard deviation of the high-achieving girls' share is 0.203 and the corresponding share for boys is 0.193 (see Table 1). When we control for primary school and middle school class fixed effects and for average class characteristics, the residual variation of the girls' and boys' share is, respectively, 0.136 and 0.129. Overall, despite the inclusion of school and class controls reduces the shares' variation, it appears that there is enough variation left in the variables of interest.

We now provide evidence supportive of the lack of sorting within primary school classes. First, we check whether average observable students' characteristics significantly differ between classes of the same primary school. Formal tests based on data collapsed at the class level are reported in Figures 3 and 4. For each class characteristic (i.e. socio-economic background, share of girls, of migrants, of students with regular attendance), we run 10,000 replications of class-level regressions where each class characteristic is regressed on primary school class (*section*) dummies and primary school fixed effects. In each replication, we randomly rank classes within schools and use the first ranked class as the reference category.

For each observable characteristic, Figure 3 shows the distribution of the p-values of the F test for the joint significance of the class dummies in the 10,000 replications of the regressions. In case of random assignment, the null hypothesis that the coefficients of the class dummies are jointly zero at the 5 percent significance level should be rejected in five percent of the cases. We see that this is always true with exception of the share of migrants, for which the null hypothesis is rejected in around ten percent of cases. However, the average difference between the class dummies coefficients when the dependent variable is the class share of migrants is negligible in economic terms. Appendix Figure 4 shows the distributions of the weighted averages of the absolute value of the class dummies coefficients from the 10,000 replications of class-level regressions. It shows that on average the estimated differences in observable characteristics between classes of a given primary school are in general very small. In the case of the migrant share, the 99^{th} percentile of the average coefficients' value in the 10,000 replications implies a negligible change in the average number of migrant students per class from 1.64 to just 1.72.

As a second balancing check, we follow Lavy and Schlosser (2011) and we show the correlation between the class shares of high-achieving girls and boys with a number of observable predetermined individual characteristics, including citizenship, parental background and regular attendance.

Specifically, we regress parental background and dummies for migrant and for regular attendance on the class share of high-achieving girls and boys, including primary school and middle school class fixed effects. Given that specific individual characteristics like citizenship or parental background are correlated with the probability of being a high achiever, a mechanical correlation between the high-achieving shares and specific individual characteristics is possible considering that we computed the leave-one-out shares of high achievers (Guryan et al. 2009). In view of this, we include controls for high achiever interacted with the girl/boy dummy in the regressions on the share of respectively, high achieving girls and boys. Results in Table 2 show a very low and insignificant association between all considered individual characteristics and both boys (Panel A) and girls (Panel B) share of high-achievers in the class. This evidence reassures us that the within-school/between-classes variation in the share of male and female high-achievers is not related to the variation in individual observable characteristics. Obviously, students' sorting may be based on individual unobserved characteristics. However, the lack of correlation between our variables of interest and individual observable characteristics above outlined suggests that we can reasonably assume a similar lack of correlation with unobservables, especially when they are correlated with observables (Altonji, Elder, and Taber 2005).

Overall, all the previous tests support the absence of students' sorting across classes within primary schools for students belonging to the same middle school class. This evidence corroborates our identifying assumption that, conditional on the included sets of fixed effects, the primary school gender-specific shares of high-achieving classmates is as good as random.

4 Results

This section presents our main results on individual outcomes. Section 4.1 shows how the class share of own and opposite gender high achievers affects grade 8 math achievements for both girls and boys. Section 4.2 investigates the effect of high-achievers on high school track choice.

4.1 Math achievement in 8^{th} grade

Table 3 presents the main results on grade 8 math achievements (in units of standard deviations). The first specification includes only the class shares of high-achievers of both genders, their interaction with the girl dummy and the girl dummy. Descriptive results in column 1 show that higher shares of own gender high achievers in grade 5 improve grade 8 math achievements, while higher shares of opposite gender high achievers reduce it. As discussed in Section 3, however, this simple OLS model may suffer from a number of biases. For this reason, from columns (2) to (4) we progressively enrich the specification.

The specification in column 2 adds fixed effects for primary school and for middle school (8^{th} grade) class to control for any unobserved factor at both primary school and middle school class level (including, e.g., middle school teacher quality). In column 3 specification we add individual controls, namely, a dummy for migrant, fixed effects for each deciles of the grade 5 INVALSI math achievement distribution and for each centile of the distribution of the socio-economic background variable and gender specific relative ability through class math achievement rank based on grade 5 INVALSI score.[9].

As we cannot include primary school (5^{th} grade) class fixed effects given that the main source of variation of the shares of high achievers is across grade 5 classes,[10] our preferred specification in column 4 adds primary school class-specific standard controls: share of girls, share of migrants, average socio-economic parental background and class size. We also add the average grade 5 (rest of the) class achievement by gender based on INVALSI math scores.[11]

As regards our four variables of interest, the high-achievers shares and their interaction with the girl dummy, the sign of the coefficients is the same across the different specifications, although in some cases the size changes. Overall, the data show forceful evidence that the primary school share of gender-specific high achievers matters for subsequent academic performance. To better assess such relationship, Figure 5 visualizes the point estimates of the coefficients of the share variables and of their interactions with the girl dummy along with their confidence intervals based on the full specification of column 4 of Table 3. The first interesting result is that the share of own-gender high-achievers in primary school is positively related to middle school academic performance for both boys and girls. As to boys, an increase in one standard deviation in the share of male high achievers in grade 5 (i.e. an increase of 0.193) raises the math score of males in grade 8 by 0.0208 of a standard deviation. Given that the standard deviation of the males math score is 20.588 (see Table 1), this translates into an increase in the grade 8 math score of 0.43 points, which is 0.7% of the boys 8^{th} grade mean score. Turning to girls, an increase in one standard deviation in the share of female high achievers in grade 5 (i.e. an increase of 0.203) raises the math score of females in grade 8 by 0.0241 of a standard deviation. Using again the figures in Table 1, this is an increase in the grade 8 math score of 0.49 points, which is 0.9% of the females 8^{th} grade mean score.

[9]Recent literature has shown that achievement rank affects several educational outcomes including achievement and school choice (Elsner and Isphording, 2017; Denning et al., 2018; Elsner et al., 2018; Delaney and Devereux, 2019; Murphy and Weinhardt, 2020)

[10]There is just a small variation in the shares of high achievers within-grade 5 class given that they are computed using the leave-one-out rule.

[11]With exception of class size, we compute all class variables for student i with the "leave one out" rule, that is excluding student i from the computation.

The second result is that middle school math achievement is negatively affected by early exposure to high achievers of opposite gender. Specifically, as shown in Table 3 and Figure 5, an increase in one standard deviation in the share of male high achievers in primary school class (i.e. an increase of 0.193) lowers the girls math score in grade 8 by 0.0184 of a standard deviation, which is equivalent to a reduction in the females grade 8 math score of 0.372, or 0.7% of the females mean score. Symmetrically, an increase in one standard deviation in the share of primary school class female high achievers (i.e. an increase of 0.203) lowers the boys math score in grade 8 by 0.0141 of a standard deviation, a drop in the grade 8 math score of 0.29, which is 0.5% of the boys' mean score.

To explore the magnitude of the effect, Figure 6 shows the gender gap in math (in grade 8) – that is the partial derivative of equation (1) with respect to the girl variable – as a function of the share of high achieving girls and for two different levels of the shares of high achieving boys. It shows that the gender gap is non negative for girls in primary school classes in which the share of high achieving boys is at the 10^{th} percentile, growing from around 0 when the share of high achieving girls is one standard deviation below the mean to 10 percentage points when the share of high achieving girls is one standard deviation above the mean. In contrast, the gender gap for girls in primary school classes in which the share of high achieving boys is at the 90^{th} percentile turns positive only for very high levels of the share of high achieving girls (more than one standard deviation above the mean). This evidence implies that relocating a girl from a class with a substantial share of high achieving boys (e.g. at the 90^{th} percentile) and a low share of high achieving girls (e.g. one standard deviation below the mean) to a symmetric class with a low share of high achieving boys (e.g. at the 10^{th} percentile) and a substantial share of high achieving girls (e.g. one standard deviation above the mean) would generate a considerable increase in her 8^{th} grade math score from 10 percentage points below the male average to 10 percentage points above it, i.e. from 51.163 to 62.532.

Differential effect by exposure to high-achievers and by ability

A relevant question is whether our results are related to an enduring influence of exposure to high achievers on future outcomes or, instead, the effects that we found are driven by students who are continuously exposed to the same high achievers in both primary and middle school. In Italy, usually students are reshuffled when moving from primary to middle school and they have few peer in common with their primary school classmates. However, especially in small villages, it is possible that the class composition does not change much across educational stages because there are few classes in each stage. In our data, 15 percent of middle school students have no peer in common with primary school and, on average, the share of new peers in middle school classes is 80.7 percent.

This implies that most students have no interactions with their middle school peers before they start middle school, reducing concerns about reflection.

To examine this issue, we estimate our baseline equation allowing for differential shares' effects for students that in their grade 8 class have or do not have at least one primary school high achieving classmate. Figure 7 shows that the results of a positive/negative effect of exposure to own/opposite gender high-achievers is confirmed for both groups. However, as expected, the positive effect is significantly higher for students (both girls and boys) with at least one high achieving peer from primary school in the same middle school class. Still, although smaller, the effects are positive and significant also for students without primary school high achievers in the middle school class, suggesting that (part of) the positive effect of exposure to own gender high achievers is lasting and cannot be ascribed to a standard contemporaneous peer effect. The negative effect of exposure to high achievers of different gender in confirmed for both boys and girls, and there are no differences according to whether primary school high achievers are still present in middle school or not. This is an important set of results as it shows that the effects found in the baseline estimates cannot be (fully) ascribed to the direct exposure of kids to the grade 5 high achievers also in the subsequent middle school stage and, then, that they are at least partly related to lasting peer effects. We discuss potential channels in Section 6.

To understand whether our results are driven by students with specific ability levels, we now allow for heterogeneous effects by ability, i.e. by INVALSI math achievement in grade 5. Figure 8 shows results separately for students below the first quartile, between the first and third quartile and above the third quartile of grade 5 math achievement. Interestingly, this disaggregation allows us to uncover a larger positive influence of the own gender high-achievers for the students in the middle of the achievement distribution (especially in the case of girls), and a smaller positive influence for the students in the upper and lower tails of the distribution. Thus, high- and low-ability students seem to be less sensitive to the stimulus provided by high achievers of the same gender, plausibly because the former group already belongs to the upper tail of the distribution and perform well in any case, and the latter lacks the necessary skills/abilities to obtain high achievement despite being exposure to very good peers of own gender. As to the negative influence of high achievers on the opposite gender, there are no significant differences by achievement for girls, while high-ability boys appear to be more negatively affected by high performing girls compared to other boys.

Overall, the above results show that early exposure to a high share of high achievers of own/different gender leads to, respectively, better/poorer later achievement, also for students who do not have any primary school high achievers in the same middle school class and more intensely for students with intermediate ability.

4.2 High school choice

We next explore how the exposure to high achievers in primary school affects the high school track choice. Our outcome here is the likelihood of enrolling in the scientific *liceo* subtrack. As mentioned in Section 2.1, the *liceo* track is more academic and attracts higher achieving students; within the *liceo* subtracks, the scientific one is considerably more focussed on scientific subjects (math and science) compared to the other subtracks.

Table 4 shows the estimation results using the same specifications as in Table 3. Overall, we see a similar pattern to the one observed when we consider grade 8 math achievement as outcome, although the effect sizes are different. To better assess the results, we focus on our preferred full specification of column 4 of Table 4, and in Figure 10 we show the coefficients of our variables of interest and their interactions with the girl dummy. Consistent with our previous results, we find a positive effect of primary school exposure to high achieving classmates of own gender on the probability to choose the scientific *liceo* subtrack for both boys and girls. The effect size is, however, small, especially for girls, for which a one standard deviation increase in the share of female high achievers is related to an increase of 0.006 of a standard deviation (0.419) in the probability of enrolling in the scientific *liceo* subtrack, that amounts to 1.1 percent of its average value (0.226). The effect size is higher for boys, as one standard deviation increase in the share of own gender high achievers is related to an increase in the same probability of 0.013 standard deviations (0.467), corresponding to 2 percent of its average value (0.321).

The negative effect of the exposure to opposite gender high achievers is confirmed as well. In this case, the magnitude of the effect is quite small and very similar for girls and boys. Specifically, one standard deviation increase in the share of opposite gender high achievers reduces the probability to choose the scientific *liceo* track for boys and girls by, respectively, 0.007 and 0.008 of its standard deviation.

To further assess how the gender gap in the probability to enroll in an academic high school focussed on scientific subjects is affected by early exposure to high achievers in math, in Figure 11 we perform a similar exercise to the one we performed for math achievement. We look at how the gender gap evolves with the share of female high achievers for two groups of students, namely, those belonging to primary school classes with, respectively, a share of high achieving boys at the 10^{th}

and 90^{th} percentile. The evidence presented shows that the gender gap narrows as the share of high performing girls increases, although it closes down only when the share of high achieving girls is as high as three standard deviations above the mean and the share of high achieving boys is very low.

Differential effect by exposure to high-achievers and by ability

As we did in the case of grade 8 math achievement, we separate the effects by partitioning students according to whether they have or not one primary-school high-achiever in own middle school class. Figure 12 confirms that the positive effect of own gender high achievers are larger for students (both boys and girls) that continue to be exposed to at least one primary-school high achiever in the middle school. Interestingly, for girls without any primary-school high achiever in the current class, the effect is close to zero and not statistically significant. This shows that, as far as girls are concerned, the positive effect of being exposed to high share of high-achieving girls in grade 5 is not enough to induce girls to choose the math-intensive high school track, unless they keep being exposed to at least one grade 5 high-achieving girl also during middle school. Instead, the negative effect of the share of high achievers of opposite gender is present both for the students that have at least one primary-school high-achiever in their own middle school class and for those that do not. These results suggest that we can rule out the possibility that high-school choices are influenced by continuing exposure to high achievers during the middle school stage with the exception, mentioned above, of the effect of high-achieving girls on girls.

Again as for grade 8 math achievement, we split students in three groups by ability, namely high (above the 75^{th} percentile of the grade 5 math achievement), medium (between the 50^{th} and 75^{th} percentile) and low (below the 25^{th} percentile) achievement. The results in Figure 13 shows that the positive effect of own gender high-achieving peers on the probability to choose the scientific high school track is limited to girls in the middle and in the bottom of the achievement distribution and to boys above the 25^{th} percentile. As to the negative effect of opposite gender high-achievers, it basically does not vary by baseline achievement for girls, while it is significant only on the medium- and high-ability group for boys.

Overall, our results on both outcomes suggest that middle-ability kids seem the most sensitive to the influence of high achievers compared to low and high ability kids who, for opposite reasons, may have smaller margins of improvement/deterioration.

5 Robustness and sensitivity

We perform 5 robustness/sensitivity checks of our main findings. The results are shown in Tables 5 and 6. The former shows results when we consider grade 8 math achievement as outcome, while the latter refers to high school track choice.

The first two columns of the tables replicate our main estimation for different samples obtained including students belonging to classes of different size. Our main estimates in Table 3 are based on the sample of students in classes between 10 and 27, corresponding to a 2.8% drop of the observations. In the first column of Tables 5 and 6, we show estimates obtained on the full sample, then including also very small and very large classes. In the second column, considering that the Italian law requires that the number of pupils allowed for each primary school class has to be between 15 and 26,[12] we restrict further the sample with respect to the baseline considering only classes with the size prescribed by the law, corresponding to a 12% drop of the observations. In both cases, the sample variation does not imply a change in the size or the significance of the shares' coefficients in both the grade 8 math achievement (Table 5) and the high school track choice estimates (6).

In column 3 of Tables 5 and 6 we test the robustness of our results using a different definition of high-achiever, namely, considering high achiever a student who got a mark at least equal to 8 instead of 9. We find that all the shares' effect are confirmed for both outcomes; the coefficients of own gender shares are slightly smaller compared to when we define as high achievers students with a mark at least equal to 9, and this suggests that higher achieving classmates inspire more towards better performance and scientific high school choice. We also find a slightly larger negative effect of opposite gender high achievers.

We further test the robustness of our results excluding the control for grade 5 math achievement from the estimated equation because it can be considered an outcome of the primary school exposure to high achievers and it may capture some of the relationship between such exposures and our outcomes. We expect to find a higher size of the effect of our variables of interest because it is likely that the impact of exposure to high achievers during primary school on later outcomes is largely channelled by higher achievement in primary school. Results in column 4 confirm qualitatively all our results but the size of the effects is considerably higher compared to our baseline specification. This evidence indicates that the relationship between exposure to good peers and outcomes goes also through grade 5 achievement. However, our baseline results indicates that this relationship is still

[12]In some cases the number of pupils per class can be lower (e.g. in mountain villages or small islands or in classes with disabled pupils) or higher (if there are residual pupils within the school), although in theory they cannot be more than 27.

there when controlling for primary school achievement.

Finally, we consider that test scores may be altered by illicit behavior aimed at increasing students' performance. With this respect, INVALSI computes for each class an index measuring potential cheating considering factors such as the class mean score and its standard deviation, the homogeneity of answers and the number of missing answers. INVALSI makes available this index that allows computing test scores corrected for cheating. In column 5 of Table 5 we re-estimate our model for middle school achievement using as outcome variable the grade 8 math achievement corrected for cheating. We see again that primary school exposure to high achievers has a positive effect on subsequent academic performance if they are of own gender, and a negative effect if they are of opposite gender. Effects size is similar to our baseline estimates.

6 Discussion, interpretation and additional results

The evidence presented above shows that girls and boys who have been exposed early in their academic career to own gender high achievers in math exhibit a better math achievement at the end of middle school and a higher probability of choosing an academic scientific high school track compared with similar peers with a lower exposure. Early exposure to a high share of high achievers of opposite gender, instead, is related to lower math achievement and probability of enrolling in a scientific *liceo*. In this section, we propose possible interpretations of our main results.

A first possible hypothesis is that being exposed in the first years of own educational path to a high share of math high achievers of own gender, who are likely closer peers than high achievers of opposite gender, may increase achievement through ability spillovers that, favoring math learning, helps developing it in the future. The story is one of enduring effects related to the acquisition of learning skills, e.g. the right study method, that improve permanently – or for a long subsequent period – academic performance and that favor the choice of the scientific high school track. However, while this is a plausible line of interpretation for the positive same-gender effect, such a spillover hardly explains the negative effect of high achievers of opposite gender.

A second possible interpretation is related to high achieving peers acting as role models. The assumption is that belonging to a group where some members perform particularly well in a specific task may induce some people belonging to that group to think that the same task is within their reach ("positive" role model). In this respect, same gender peers may act as influential role models, and exposure to high-performing peers of own gender, in addition to increasing achievement through ability spillovers, may contribute to improve students' taste for math and beliefs about their math ability and to improve academic performance through higher motivation and effort. Indeed, psychological research has shown that performance on standardized math tests is affected by one's confidence (Dar-Nimrod and Heine, 2006) and ample economic literature has shown that female role models affect educational outcomes such as academic achievement or school choices (Dee, 2007; Bettinger and Long, 2005; Hoffmann and Oreopoulos, 2009; Carrell et al., 2010; Lim and Meer, 2017; Kato and Song, 2018; Lim and Meer, 2019; Porter and Serra 2019; Breda et al., 2020). On the other hand, seeing peers of opposite gender performing particularly well in a subject may bring pupils to believe that kids belonging to that gender are more naturally gifted at that subject ("negative" role model). Although our data do not allow us to rigorously test the plausibility of the two proposed potential interpretations, all our results are consistent with the role-model reading, both in its "positive" and "negative" facet.

As a next step, we exploit the richness of our data to obtain additional results which provide suggestive evidence on how psychological mechanisms may channel the effect of high achievers on outcomes. Specifically, we use information taken from the INVALSI questionnaire administered to our cohort of students when they are in their 10^{th} grade (second year of high school) that elicit information on students' taste for math, on how they feel at ease with math and on math-specific anxiety.[13] As regards taste for math, we use four questions asking students whether they enjoy studying and learning math.[14] Using these questions, we run a principal component analysis. One factor with eigenvalue equal to 3.49 is retained loading all four components and we name it "Enjoy math". We capture ease with math through a dummy variable taking the value of one for students stating that they felt relaxed while answering the math INVALSI test. Finally, to capture math anxiety we perform a principal component analysis on three questions that allows eliciting grade 10 students' anxiety and apprehension both before and while sitting the math test.[15] One factor with eigenvalue equal to 2.02 is retained loading all three components. We name this factor "Math anxiety".

To understand whether early exposure to own and opposite gender high-achieving classmates is related to the previous variables, we estimate our main equation using them as dependent variables. We use the same specification as in Table 3, column 4, but including grade 10 instead of grade 8

[13]Psychological literature has shown that math anxiety is connected with negative attitudes concerning math, such as lack of confidence and motivation, and with math avoidance, and evidence from PISA shows that students experiencing high math anxiety achieve considerably less than non-anxious students (D'Agostino, Schirripa Spagnolo and Salvati, 2021).

[14]The questions are: "How much do you agree that you i) enjoy learning math; ii) are happy to study math; iii) are interested in learning math well; iv) like to learn new topics in math."

[15]The questions are: "Thinking about the math test, how much do you agree that i) you were worried before taking it; ii) you were so much anxious while sitting the test that you couldn't answer the questions; iii) you had the impression of doing bad while sitting the test."

class fixed effects. Results in column 1 of Table 7 document a positive relationship between exposure to high-performing classmates of own gender and subsequent taste for math. As regards exposure to high achievers of opposite gender, instead, no significant relationship emerges.

In column 2 of Table 7, we see that for both girls and boys the share of primary school own gender high achievers is positively related to the probability of feeling at ease with math. In this case we find a negative and significant relationship with opposite gender high achievers' share as well, although only in the case of boys. Finally, in the case of math anxiety the relationships with the shares of high achievers fail to reach statistical significance.

Overall, the previous findings suggest that psychological mechanisms play a role in channeling our results. They suggest that being early exposed to a high share of high achievers of own group helps creating a favorable attitude towards math that, in turn, may improve subsequent achievement and reduces math avoidance, for instance increasing the likelihood of choosing a scientific high school track. They also partly show that a high share of opposite gender high achievers reduces students' ease with math. Although positive attitudes may stem both from role model effects and from enduring effects of direct gender-specific student-to-student spillovers, recalling that the asymmetric shares' effect cannot be explained by such spillover effect, the evidence presented in this section suggests that some of our main results may be partly explained by the fact that high-achievers of own gender act as role models: seeing classmates belonging to own group (i.e. of the same gender) performing particularly well in math in an early stage of own educational process contributes to shaping positive attitudes towards math.

7 Conclusion

In this study, we examined the effect of early exposure to high achievers of own and opposite gender in math on later math achievement and on high school track choice. Our results show asymmetric effects. Specifically, both girls and boys achieve better in middle school and have a higher probability of choosing a scientific-oriented high school track when, during primary school, they belong to classes with a high share of high achievers of own gender. In contrast, students of both genders achieve less and are less likely to choose a scientific high school track if they have been exposed to a high share of high achievers of opposite gender in primary school. We show that psychological factors may play a role in explaining our results. In particular, we find that students exposed to a high share of high achievers of own gender are more likely to develop subsequent positive attitudes toward.

Our results are consistent with a role model story. Students uncertain about their subject-specific ability may be encouraged if they see someone with characteristics similar to theirs who is doing well in the subject. In contrast, seeing classmates of opposite gender doing particularly well in math may lead them to think that opposite gender peers are more naturally gifted at math compared to peers of their own gender, causing worse math attitude and subsequent poorer achievement and math avoidance.

In view of the well known gender gap in math achievement and, especially, in choice of field of study, our results suggest that policies aimed at providing girls with greater exposure to female peers achieving notably well in math may help reducing such gender gap. Moreover, although ability and achievement are not observable when forming classes in the first stage of the educational process, trying to balance as much as possible classes by gender and observable characteristics related to achievement, like parental background or citizenship, could help reducing the asymmetric negative effect of high achievers on educational outcomes.

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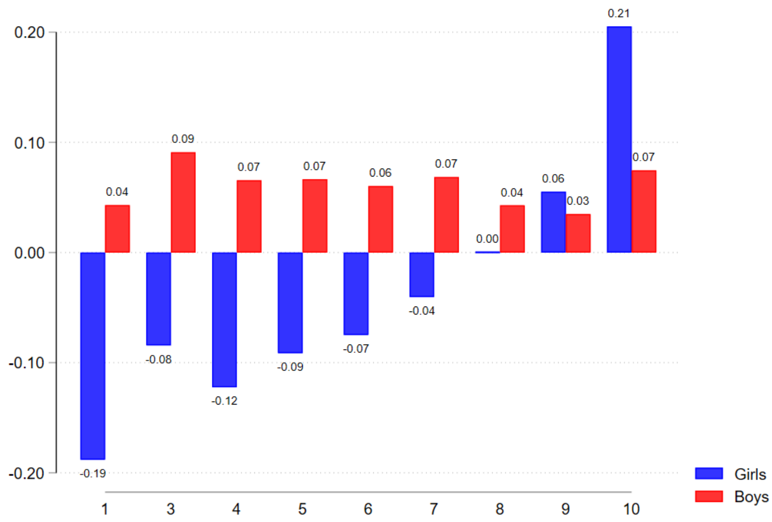
Tables and Figures

Table 1: Descriptive statistics

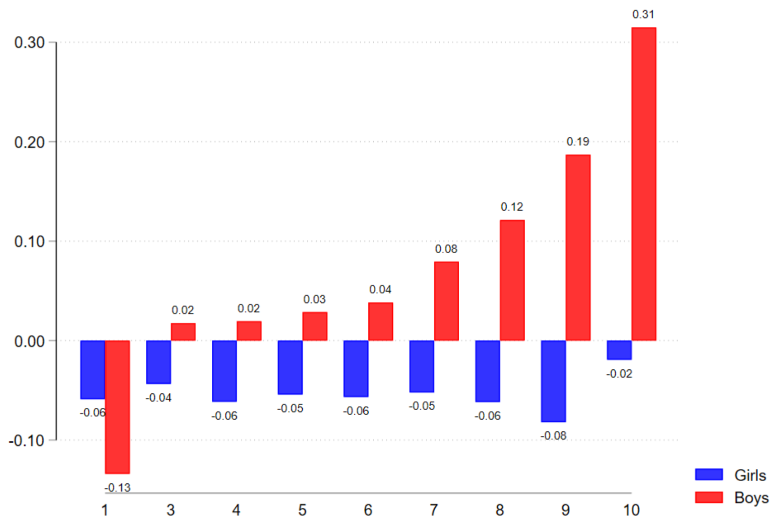
	Females	Males	Total
8^{th} grade INVALSI math score	54.578	56.848	55.703
	(20.194)	(20.588)	(20.421)
5^{th} grade INVALSI math score	58.888	62.386	60.621
	(18.719)	(18.647)	(18.765)
Enrolled in scientific *liceo*	0.226	0.321	0.272
	(0.419)	(0.467)	(0.445)
Class-level share of female high achievers	0.213	0.228	0.221
	(0.197)	(0.210)	(0.203)
Class-level share of male high achievers	0.231	0.214	0.223
	(0.198)	(0.187)	(0.193)
Girls			0.504
			(0.500)
With at least one high achiever in 8^{th} grade class	0.483	0.479	0.481
	(0.500)	(0.500)	(0.500)
Migrant	0.081	0.075	0.078
	(0.272)	(0.263)	(0.268)
Socio-economic background	0.060	0.076	0.068
	(0.988)	(0.984)	(0.986)
Unemployed parents	0.036	0.034	0.035
	(0.185)	(0.181)	(0.183)
Highly educated parents	0.275	0.281	0.278
	(0.446)	(0.449)	(0.448)
Student tools (desk, PC, etc.)	4.598	4.558	4.578
	(1.242)	(1.270)	(1.256)
Regular age	0.966	0.967	0.966
	(0.181)	(0.179)	(0.180)
Gender-specific rank	0.479	0.490	0.485
	(0.314)	(0.310)	(0.312)
N	177,206	174,071	351,277

Note: The table shows for each variable averages and standard deviations in parentheses. The total number of observations for the dummy "Enrolled in scientific *liceo*" is 290,191, (149,467 for females and 140,724 for males). Migrant is a dummy equal to one if the student has a foreign citizenship. ESCS is a standardized variable provided by INVALSI which measures students' economic, social and cultural status, as in OECD Pisa, and considers parental education, occupation, and home resources. Unemployed parents is a dummy equal to one if at least one of the parents is unemployed. Educated parents is a dummy equal to one if at least one of the parents has (at least) a high-school diploma. Students tools is the number of assets owned by students among a quiet place to study, a desk, a pc, an encyclopaedia, an internet connection and an own bedroom. Regular age is a dummy equal to one for students who started primary school in the year of their sixth birthday. Relative rank is the gender-specific rank in math in grade 5.

Figure 1: Standardised 8^{th} grade math scores and share of high achievers



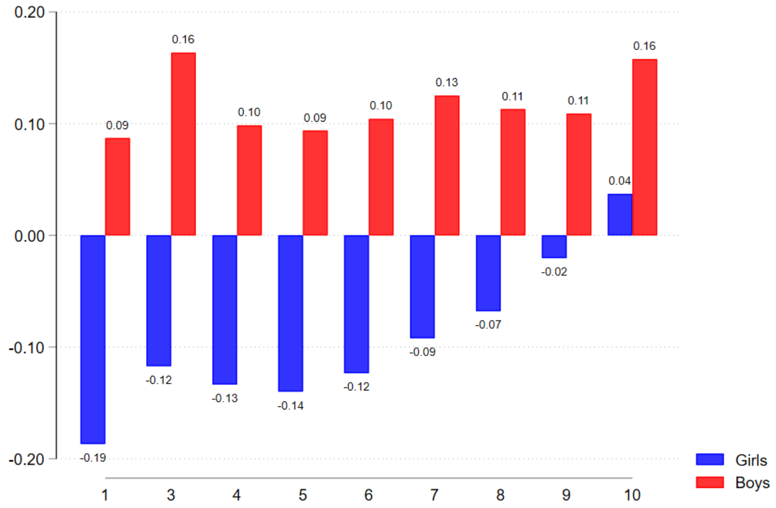
(a) Girls' share



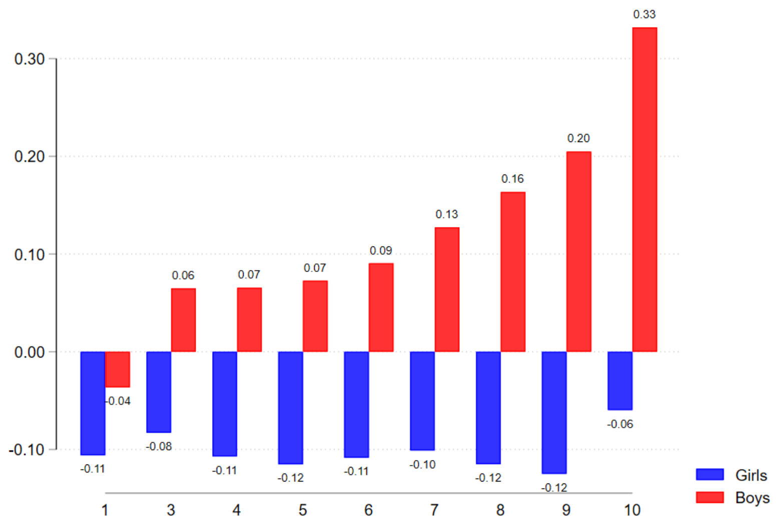
(b) Boys' share

Note: each panel shows the average girl and boy's standardized grade 8 INVALSI math score by deciles of the distribution of the leave-one-out grade 5 class share of math high achieving girls (panel a) and boys (panel b)

Figure 2: Standardised share enrolling in scientific *liceo* and share of high achievers



(a) Girls' share

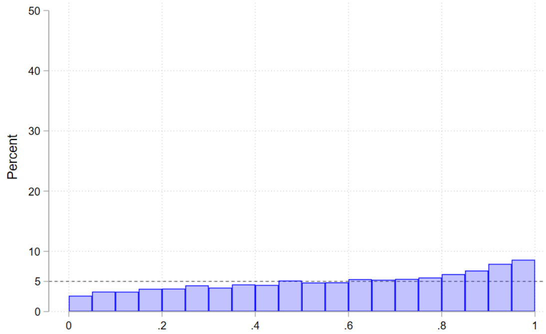


(b) Boys' share

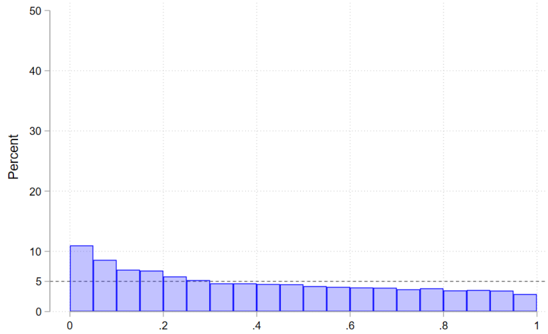
Note: each panel shows the girl and boy's standardized share enrolling in scientific *liceo* by deciles of the distribution of the leave-one-out grade 5 class share of math high achieving girls (panel a) and boys (panel b)

Balancing

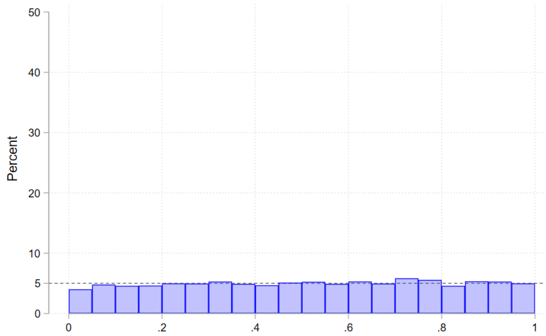
Figure 3: p-values of F-tests for joint significance of class dummies



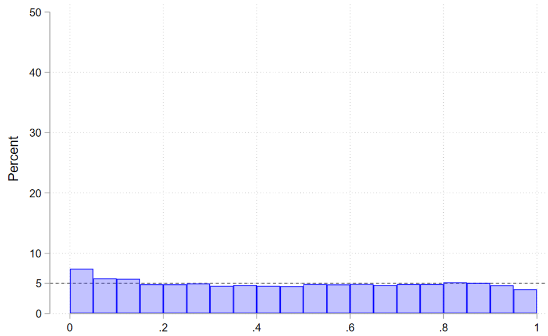
(a) Girl



(b) Migrant



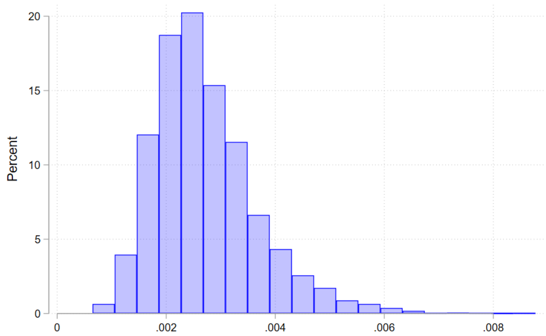
(c) Social background index



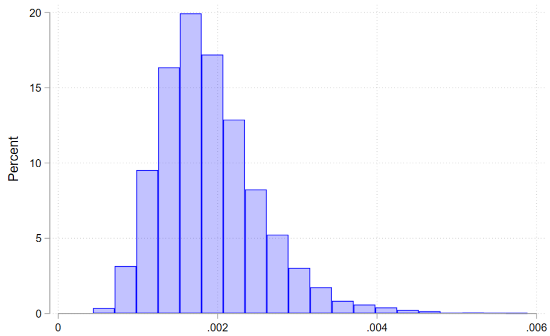
(d) Regular attendance

Note: each panel shows the distribution of the p-values of the F-tests for joint significance of class dummies from 10,000 replications of class-level regressions of class characteristics on class dummies and primary school fixed effects. Class dummies are obtained as follows. First, classes are randomly ranked within schools and then each class is assigned a dummy according to its within-school ranking. In each of the 10,000 replications, classes are randomly re-ranked within schools.

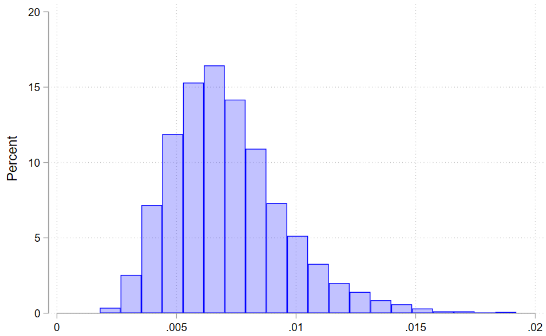
Figure 4: Weighted averages of class dummies coefficients



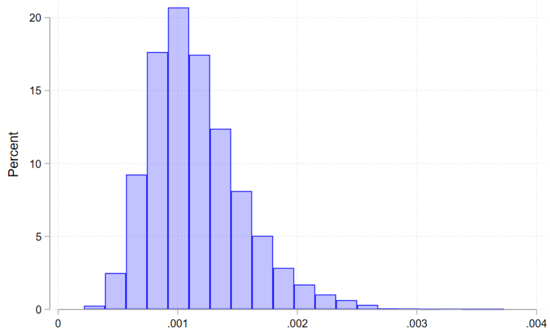
(a) Girl



(b) Migrant



(c) Social background index



(d) Regular attendance

Note: each panel shows the distribution of the weighted averages of the absolute value of the coefficients of class dummies from 10,000 replications of class-level regressions of class characteristics on class dummies and primary school fixed effects. Class dummies are obtained as follows. First, classes are randomly ranked within schools and then each class is assigned a dummy according to its within-school ranking. In each of the 10,000 replications, classes are randomly re-ranked within schools.

Table 2: Conditional correlation between high-achiever shares and observable students' characteristics

VARIABLES	(1) Migrant dummy	(2) Individual socio-economic background	(3) Regular attendance
		Panel A: boys	
Share of top boys in math in 5^{th} grade	-0.0005	0.0008	-0.0004
	(0.0007)	(0.0027)	(0.0005)
High achiever × boy	-0.0381***	0.2884***	0.0113***
	(0.0013)	(0.0052)	(0.0009)
		Panel B: girls	
Share of top girls in math in 5^{th} grade	-0.0000	0.0001	-0.0006
	(0.0007)	(0.0027)	(0.0005)
High achiever × girl	-0.0343***	0.3035***	0.0071***
	(0.0014)	(0.0053)	(0.0010)
Observations	351,277	351,277	351,167
Primary school FE	YES	YES	YES
8^{th} grade class FE	YES	YES	YES
Individual controls	NO	NO	NO
Class controls	NO	NO	NO

Note: Each column reports estimates from separate regressions of the individual characteristics in the columns. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the primary school level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

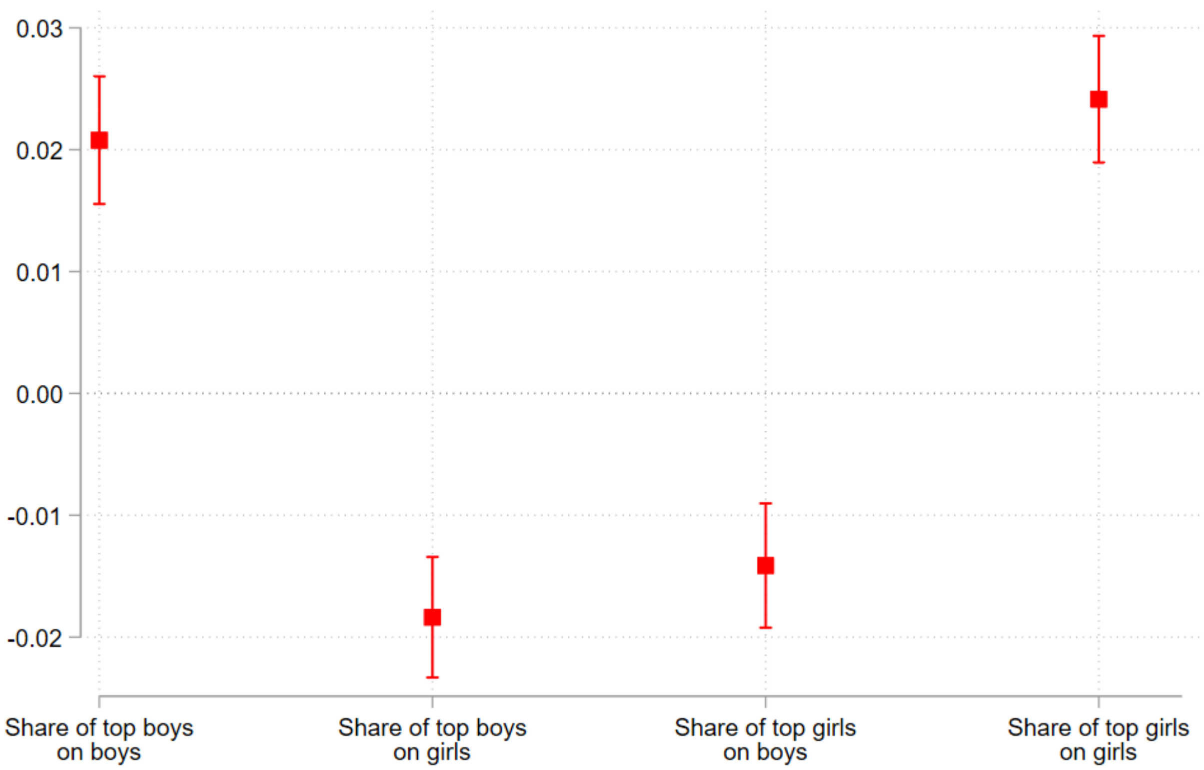
Effects on 8^{th} grade math scores

Table 3: Effect of high achievers on 8^{th} grade math scores

VARIABLES	(1) 8^{th} grade math score	(2) 8^{th} grade math score	(3) 8^{th} grade math score	(4) 8^{th} grade math score
Share of top girls in math in 5^{th} grade	-0.0273***	-0.0573***	-0.0364***	-0.0141***
	(0.0037)	(0.0031)	(0.0025)	(0.0026)
Share of top girls in math in 5^{th} grade × Girl	0.0892***	0.0838***	0.0655***	0.0383***
	(0.0039)	(0.0036)	(0.0029)	(0.0028)
Share of top boys in math in 5^{th} grade	0.0693***	0.0210***	0.0348***	0.0208***
	(0.0040)	(0.0033)	(0.0027)	(0.0027)
Share of top boys in math in 5^{th} grade × Girl	-0.0897***	-0.0810***	-0.0678***	-0.0391***
	(0.0038)	(0.0036)	(0.0028)	(0.0028)
Girl dummy	-0.1120***	-0.1093***	-0.0144***	0.0081***
	(0.0038)	(0.0037)	(0.0028)	(0.0027)
Observations	351,277	351,277	351,277	351,277
R-squared	0.0064	0.2975	0.6078	0.6173
Primary school FE	NO	YES	YES	YES
8^{th} grade class FE	NO	YES	YES	YES
Individual controls	NO	NO	YES	YES
Class controls	NO	NO	NO	YES
Coeff: share of top girls (1+Girl)	0.0620	0.0265	0.0290	0.0241
F-test: share of top girls (1+Girl)	222.3	66.80	119	82.90
$P > F$: Share of top girls (1+Girl)	0	0	0	0
Coeff: share of top boys (1+Girl)	-0.0205	-0.0599	-0.0330	-0.0184
F-test: share of top boys (1+Girl)	28.61	413.8	173.1	52.94
$P > F$: Share of top boys (1+Girl)	9.22e-08	0	0	0

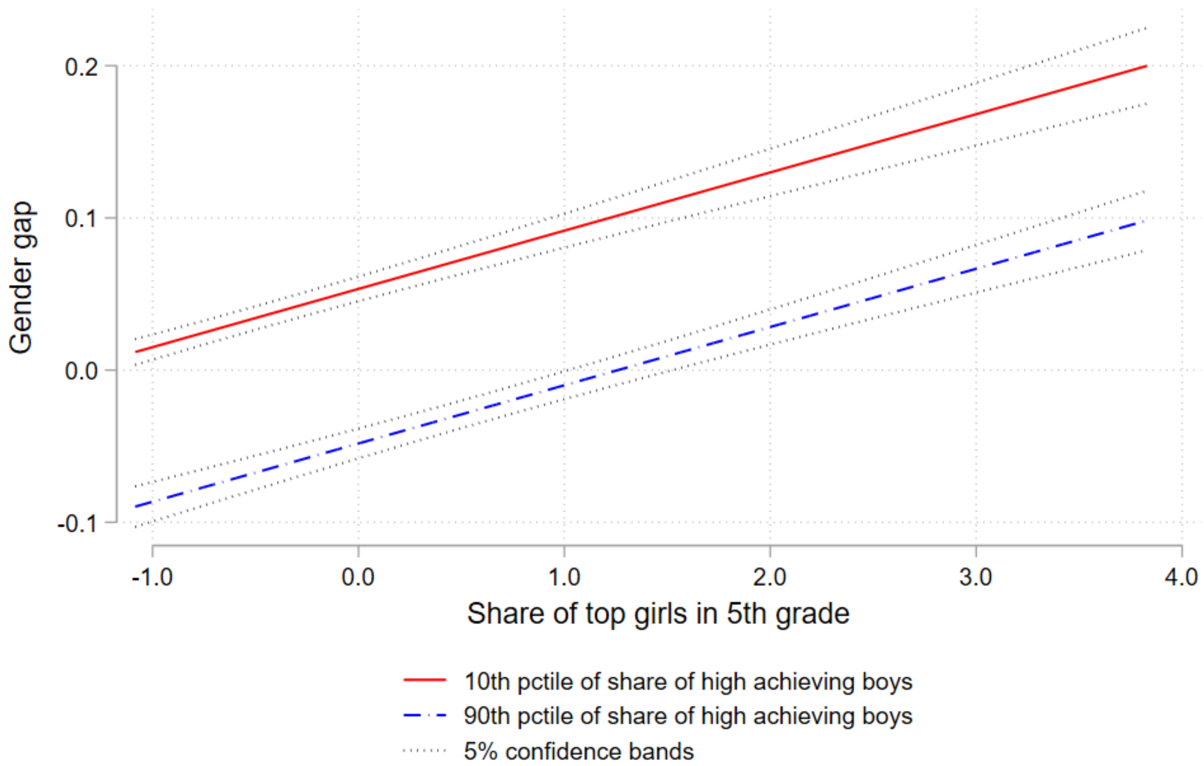
Note: Individual controls include fixed effects for each decile of the distribution of 5^{th} grade math scores, fixed effects for each decile of the distribution of socio-economic score (ESCS), a dummy for migrant and 5^{th} grade gender-specific rank in math in grade 5. Class controls include the (leave-one-out) share of girls, the (leave-one-out) share of migrants, the (leave-one-out) average socio-economic score, the (leave-one-out) gender-specific average math score, and the 5^{th} grade class size. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the 5^{th} grade school level and at the 8^{th} grade class level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Figure 5: Effect of high achievers on 8^{th} grade math scores



Note: This figure shows the effect of the share of own and opposite gender high achievers on girls and boys' grade 8 math achievement based on the estimates reported in Table 3 (column 4)

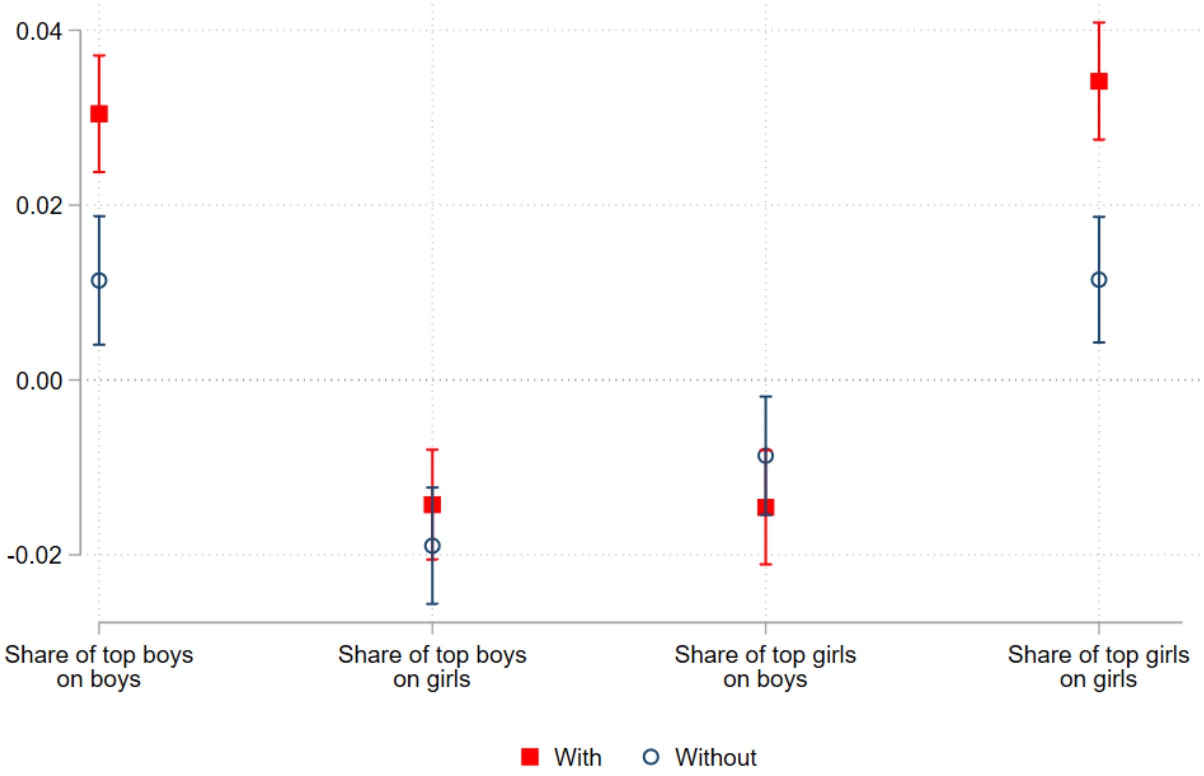
Figure 6: 8^{th} grade math achievement gender gap



Note: this figure shows the gender gap in grade 8 math achievement based on the estimates reported in Table 3 (column 4). The share of top girls in 5^{th} grade has been demeaned and is expressed in units of standard deviations.

Heterogeneous effects on 8^{th} grade math scores

Figure 7: Heterogeneous effects on 8^{th} grade math scores for kids with and without high achievers from primary school in 8^{th} grade



Note: This figure shows the effect of the share of own and opposite gender high achievers on girls and boys' grade 8 math achievement based on the estimates reported in Table A1

Figure 8: Heterogeneous effects by 5^{th} grade math score

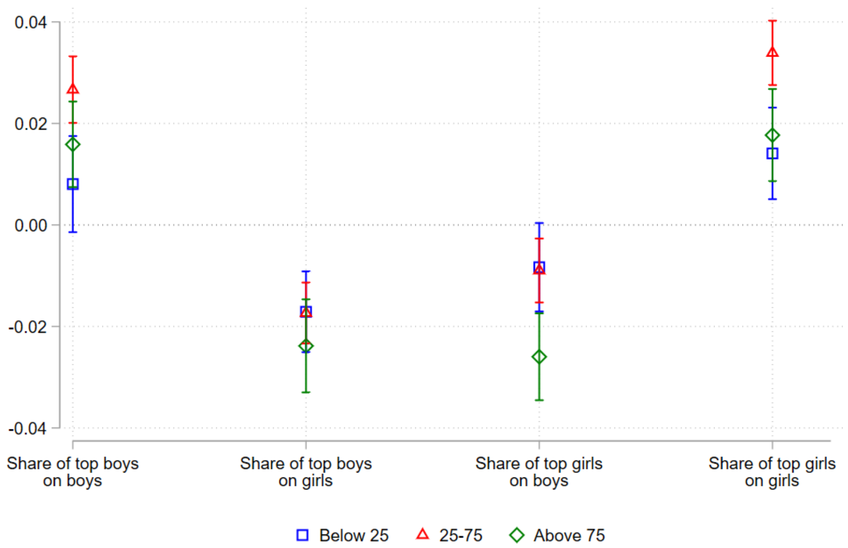


Figure 9: Bottom quartile, interquartile range and top quartile of the 5^{th} grade math score

Note: This figure shows the effect of the share of own- and opposite-gender high achievers on girls and boys' grade 8 math achievement based on the estimates reported in Table A2

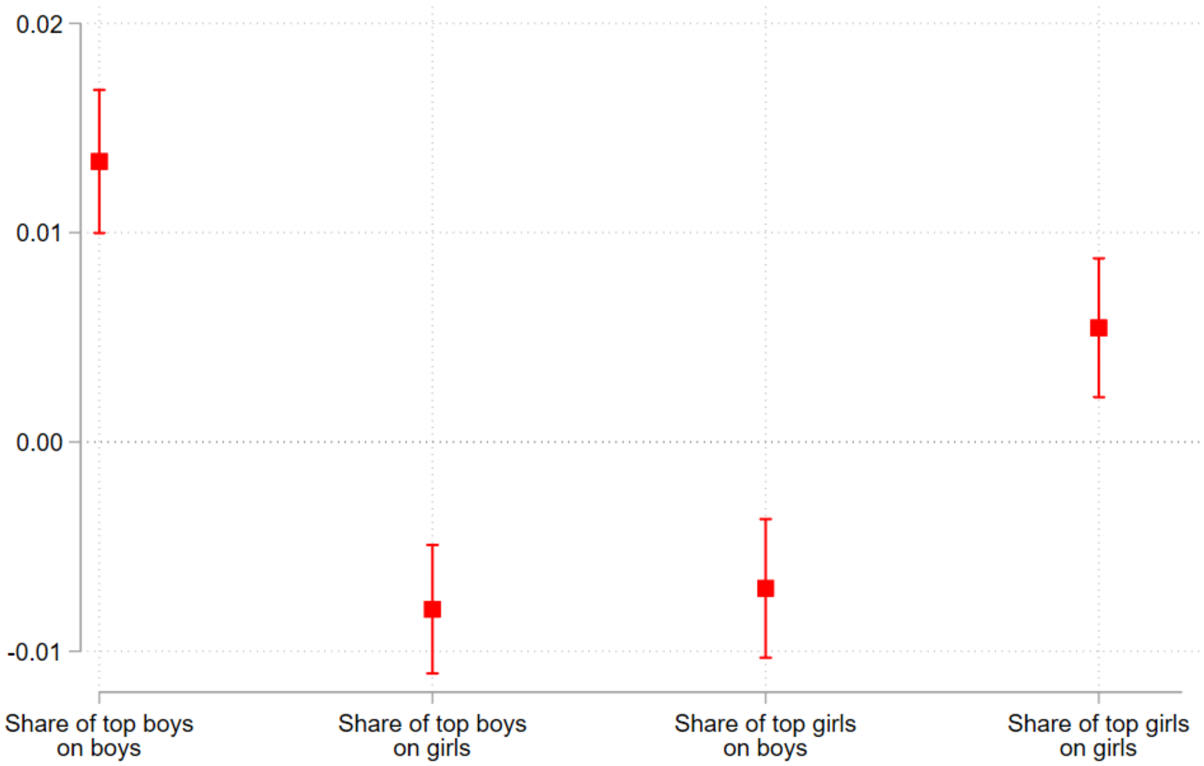
Effects on the probability to choose ***Liceo Scientifico***

Table 4: Effect of high achievers on the probability to enroll in scientific *liceo*

VARIABLES	(1) Liceo scientifico	(2) Liceo scientifico	(3) Liceo scientifico	(4) Liceo scientifico
Share of top girls in math in 5^{th} grade	-0.0051***	-0.0155***	-0.0104***	-0.0070***
	(0.0017)	(0.0017)	(0.0016)	(0.0017)
Share of top girls in math in 5^{th} grade × Girl	0.0228***	0.0224***	0.0179***	0.0124***
	(0.0020)	(0.0021)	(0.0020)	(0.0020)
Share of top boys in math in 5^{th} grade	0.0269***	0.0128***	0.0161***	0.0134***
	(0.0019)	(0.0018)	(0.0016)	(0.0017)
Share of top boys in math in 5^{th} grade × Girl	-0.0320***	-0.0302***	-0.0271***	-0.0214***
	(0.0020)	(0.0021)	(0.0020)	(0.0020)
Girl dummy	-0.0950***	-0.0941***	-0.0697***	-0.0652***
	(0.0020)	(0.0021)	(0.0020)	(0.0020)
Observations	289,960	289,960	289,960	289,960
R-squared	0.0134	0.1782	0.2729	0.2752
Primary school FE	NO	YES	YES	YES
8^{th} grade class FE	NO	YES	YES	YES
Individual controls	NO	NO	YES	YES
Class controls	NO	NO	NO	YES
Coeff: share of top girls (1+Girl)	0.0177	0.00687	0.00750	0.00545
F-test: share of top girls (1+Girl)	132.3	16.92	21.81	10.41
$P > F$: Share of top girls (1+Girl)	0	3.95e-05	3.08e-06	0.00126
Coeff: share of top boys (1+Girl)	-0.00506	-0.0174	-0.0110	-0.00799
F-test: share of top boys (1+Girl)	13.43	131.9	58.05	26.04
$P > F$: Share of top boys (1+Girl)	0.000249	0	0	3.46e-07

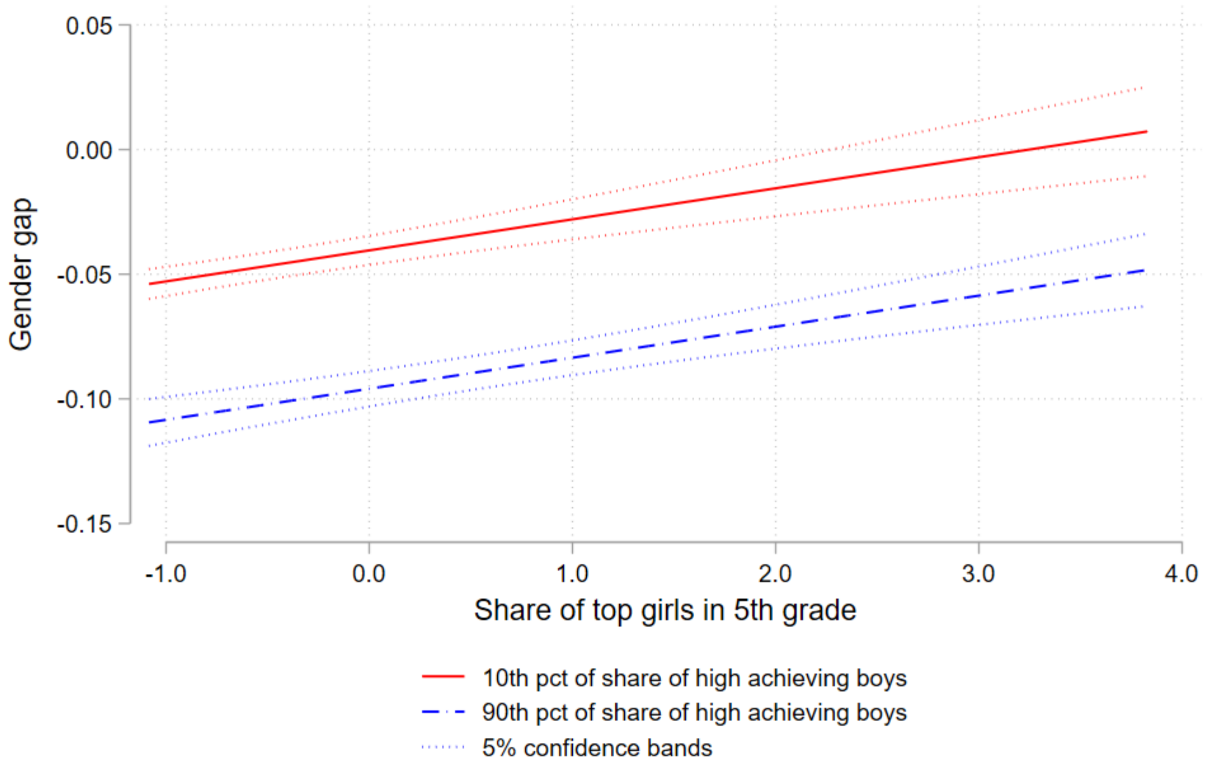
Note: Individual controls include fixed effects for each decile of the distribution of 5^{th} grade math scores, fixed effects for each decile of the distribution of socio-economic score (ESCS), a dummy for migrant and 5^{th} grade gender-specific rank in math in grade 5. Class controls include the (leave-one-out) share of girls, the (leave-one-out) share of migrants, the (leave-one-out) average socio-economic score, the (leave-one-out) gender-specific average math score, and the 5^{th} grade class size. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the 5^{th} grade school level and at the 8^{th} grade class level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Figure 10: Effect of high achievers on the probability to enroll in scientific *liceo*



Note: this figure shows the effect of the share of own and opposite gender high achievers on girls and boys' probability to enroll in scientific *liceo* based on the estimates reported in Table 4

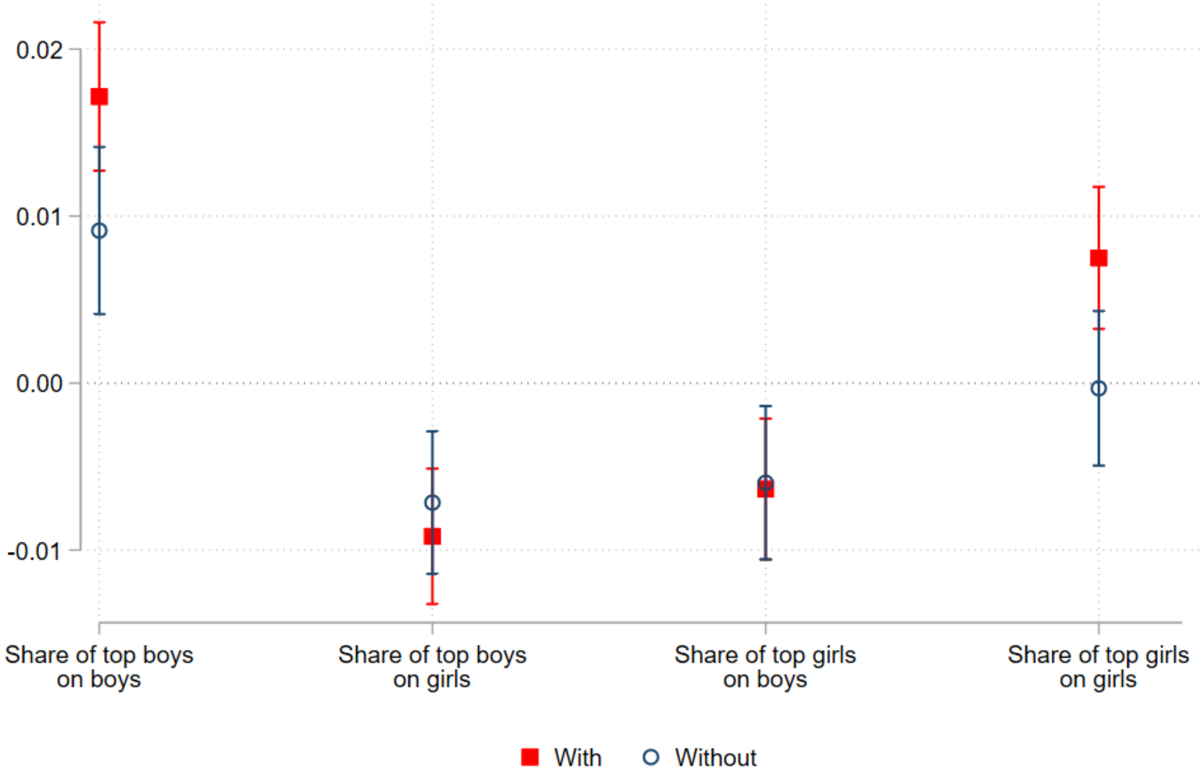
Figure 11: Gender gap in the probability to enroll in scientific *liceo*



Note: this figure shows the gender gap in the probability to enroll in scientific *liceo* based on the estimates reported in Table 4 (column 4). The share of top girls in 5^{th} grade has been demeaned and is expressed in units of standard deviations.

Heterogeneous effects on the probability to choose ***Liceo Scientifico***

Figure 12: Heterogeneous effects on the probability to choose scientific *liceo* for kids with and without high achievers from primary school in 8^{th} grade



Note: This figure shows the effect of the share of own and opposite gender high achievers on girls and boys' probability to choose scientific *liceo* based on the estimates reported in Table A3

Figure 13: Heterogeneous effects on the probability to choose scientific *liceo* by 5^{th} grade math score

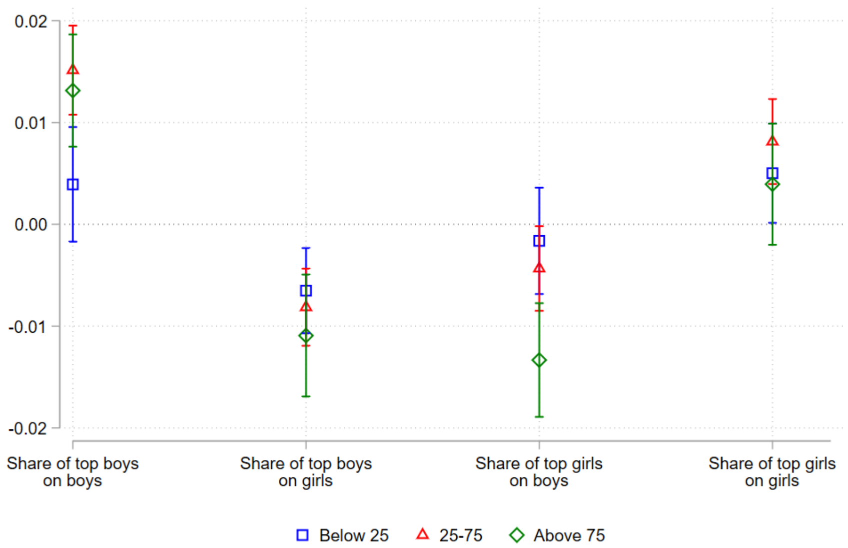


Figure 14: Bottom quartile, interquartile range and top quartile of the 5^{th} grade math score

Note: This figure shows the effect of the share of own- and opposite-gender high achievers on girls and boys' probability to choose scientific *liceo* based on the estimates reported in Table A4

Robustness checks

Table 5: Robustness (8^{th} grade math achievement)

VARIABLES	(1) Full sample	(2) 14 < Class size < 27	(3) High achievers from 8	(4) No math score FE	(5) Correction for cheating
Share of top girls in math in 5^{th} grade	-0.0134***	-0.0153***	-0.0197***	-0.0773***	-0.0128***
	(0.0025)	(0.0028)	(0.0025)	(0.0028)	(0.0027)
Share of top girls in math in 5^{th} grade × Girl	0.0376***	0.0399***	0.0407***	0.1536***	0.0331***
	(0.0028)	(0.0030)	(0.0027)	(0.0033)	(0.0029)
Share of top boys in math in 5^{th} grade	0.0205***	0.0191***	0.0147***	0.0792***	0.0163***
	(0.0026)	(0.0028)	(0.0026)	(0.0029)	(0.0028)
Share of top boys in math in 5^{th} grade × Girl	-0.0383***	-0.0384***	-0.0346***	-0.1567***	-0.0340***
	(0.0028)	(0.0030)	(0.0027)	(0.0033)	(0.0029)
Girl dummy	0.0079***	0.0075***	0.0080***	-0.0887***	0.0126***
	(0.0027)	(0.0029)	(0.0027)	(0.0033)	(0.0028)
Observations	361,329	318,797	351,277	351,277	351,277
R-squared	0.6170	0.6195	0.6173	0.5567	0.5896
Primary school FE	YES	YES	YES	YES	YES
8^{th} grade class FE	YES	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES	YES
Class controls	YES	YES	YES	YES	YES
Coeff: share of top girls (1+Girl)	0.0242	0.0246	0.0210	0.0762	0.0203
F-test: share of top girls (1+Girl)	87.12	74.61	66.61	732.1	53.83
$P > F$: Share of top girls (1+Girl)	0	0	0	0	0
Coeff: share of top boys (1+Girl)	-0.0178	-0.0193	-0.0199	-0.0776	-0.0177
F-test: share of top boys (1+Girl)	52.17	51.08	65.08	818	45.99
$P > F$: Share of top boys (1+Girl)	0	0	0	0	0

Note: Individual controls include fixed effects for each decile of the distribution of 5^{th} grade math scores, fixed effects for each decile of the distribution of socio-economic score (ESCS), a dummy for migrant and 5^{th} grade gender-specific rank in math in grade 5. Class controls include the (leave-one-out) share of girls, the (leave-one-out) share of migrants, the (leave-one-out) average socio-economic score, the (leave-one-out) gender-specific average math score, and the 5^{th} grade class size. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the 5^{th} grade school level and at the 8^{th} grade class level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 6: Robustness (probability to enroll in scientific *liceo*)

VARIABLES	(1) Full sample Liceo scientifico	(2) 14 < Class size < 27 Liceo scientifico	(3) High achievers from 8 Liceo scientifico	(4) No math score FE Liceo scientifico
Share of top girls in math in 5^{th} grade	-0.0068***	-0.0075***	-0.0094***	-0.0209***
	(0.0016)	(0.0018)	(0.0016)	(0.0017)
Share of top girls in math in 5^{th} grade × Girl	0.0124***	0.0115***	0.0143***	0.0371***
	(0.0020)	(0.0022)	(0.0019)	(0.0020)
Share of top boys in math in 5^{th} grade	0.0136***	0.0138***	0.0113***	0.0257***
	(0.0017)	(0.0019)	(0.0017)	(0.0018)
Share of top boys in math in 5^{th} grade × Girl	-0.0215***	-0.0214***	-0.0203***	-0.0462***
	(0.0019)	(0.0021)	(0.0019)	(0.0020)
Girl dummy	-0.0648***	-0.0667***	-0.0653***	-0.0871***
	(0.0020)	(0.0022)	(0.0020)	(0.0020)
Observations	298,458	263,137	289,960	289,960
R-squared	0.2737	0.2800	0.2752	0.2607
Primary school FE	YES	YES	YES	YES
8^{th} grade class FE	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES
Class controls	YES	YES	YES	YES
Coeff: share of top girls (1+Girl)	0.00563	0.00404	0.00491	0.0162
F-test: share of top girls (1+Girl)	11.78	4.918	9.292	91.21
$P > F$: Share of top girls (1+Girl)	0.000602	0.0266	0.00231	0
Coeff: share of top boys (1+Girl)	-0.00785	-0.00756	-0.00899	-0.0205
F-test: share of top boys (1+Girl)	26.60	20.12	34.81	170.3
$P > F$: Share of top boys (1+Girl)	2.59e-07	7.43e-06	3.85e-09	0

Note: Individual controls include fixed effects for each decile of the distribution of 5^{th} grade math scores, fixed effects for each decile of the distribution of socio-economic score (ESCS), a dummy for migrant and 5^{th} grade gender-specific rank in math in grade 5. Class controls include the (leave-one-out) share of girls, the (leave-one-out) share of migrants, the (leave-one-out) average socio-economic score, the (leave-one-out) gender-specific average math score, and the 5^{th} grade class size. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the 5^{th} grade school level and at the 8^{th} grade class level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 7: Primary school high achievers, taste for math and math anxiety in grade 10

VARIABLES	(1) Enjoy (PCA)	(2) Relaxed	(3) Anxious (PCA)
Share of top girls in math in 5^{th} grade	-0.0011	-0.0034**	0.0019
	(0.0035)	(0.0016)	(0.0034)
Share of top girls in math in 5^{th} grade × Girl	0.0082*	0.0068***	-0.0066
	(0.0042)	(0.0021)	(0.0042)
Share of top boys in math in 5^{th} grade	0.0079**	0.0046***	-0.0055
	(0.0036)	(0.0016)	(0.0035)
Share of top boys in math in 5^{th} grade × Girl	-0.0077*	-0.0032	0.0007
	(0.0042)	(0.0020)	(0.0042)
Observations	267,441	272,027	271,982
R-squared	0.3030	0.2431	0.2936
Primary school FE	YES	YES	YES
10^{th} grade class FE	YES	YES	YES
Individual controls	YES	YES	YES
Class controls	YES	YES	YES
Coeff: share of top girls (1+Girl)	0.00703	0.00348	-0.00470
F-test: share of top girls (1+Girl)	4.161	4.209	1.978
$P > F$: Share of top girls (1+Girl)	0.0414	0.0403	0.160
Coeff: share of top boys (1+Girl)	0.000175	0.00137	-0.00476
F-test: share of top boys (1+Girl)	0.00292	0.670	2.087
$P > F$: Share of top boys (1+Girl)	0.957	0.413	0.149

Note: Individual controls include fixed effects for each decile of the distribution of 5^{th} grade math scores, fixed effects for each decile of the distribution of socio-economic score (ESCS), a dummy for migrant and 5^{th} grade gender-specific rank in math in grade 5. Class controls include the (leave-one-out) share of girls, the (leave-one-out) share of migrants, the (leave-one-out) average socio-economic score, the (leave-one-out) gender-specific average math score, and the 5^{th} grade class size. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the 5^{th} grade school level and at the 10^{th} grade class level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

A Appendix: Additional Tables

Table A1: Heterogeneous effects on 8^{th} grade math scores on kids with/without high achievers in 8^{th} grade

VARIABLES	(1) 8^{th} grade math score
Share of top girls in math in 5^{th} grade	-0.0087**
	(0.0034)
Share of top girls in math in 5^{th} grade × Girl	0.0201***
	(0.0044)
Share of top boys in math in 5^{th} grade	0.0114***
	(0.0037)
Share of top boys in math in 5^{th} grade × Girl	-0.0303***
	(0.0043)
With at least one high achieving in 8^{th} grade (except oneself)	-0.0092**
	(0.0041)
Girl dummy × At least one HAP	0.0063
	(0.0053)
Share of top girls in math in 5^{th} grade × At least one HAP	-0.0059
	(0.0043)
Share of top girls in math in 5^{th} grade × Girl × At least one	0.0286***
	(0.0057)
Share of top boys in math in 5^{th} grade × At least one HAP	0.0191***
	(0.0046)
Share of top boys in math in 5^{th} grade × Girl × At least one	-0.0144**
	(0.0056)
Observations	351,277
R-squared	0.6174
Primary school FE	YES
8^{th} grade class FE	YES
Individual controls	YES
Class controls	YES
Coeff: share of top girls (1 + girl)	0.0115
F-test: share of top girls (1 + girl)	9.821
$P > F$: share of top girls (1 + girl)	0.00173
Coeff: share of top girls (1 + SC)	-0.0146
F-test: share of top girls (1 + SC)	19.10
$P > F$: share of top girls (1 + SC)	1.26e-05
Coeff: share of top girls (1 + girl + SC + girl × SC)	0.0342
F-test: share of top girls (1 + girl + SC + girl × SC)	100.2
$P > F$: share of top girls (1 + girl + SC + girl × SC)	0
Coeff: share of top boys (1 + girl)	-0.0190
F-test: share of top boys (1 + girl)	31.19
$P > F$: share of top boys (1 + girl)	2.46e-08
Coeff: share of top boys (1 + SC)	0.0304
F-test: share of top boys (1 + SC)	80.40
$P > F$: share of top boys (1 + SC)	0
Coeff: share of top boys (1 + girl + SC + girl × SC)	-0.0143
F-test: share of top boys (1 + girl + SC + girl × SC)	19.80
$P > F$: share of top boys (1 + girl + SC + girl × SC)	8.79e-06

Note: Individual controls include fixed effects for each decile of the distribution of 5^{th} grade math scores, fixed effects for each decile of the distribution of socio-economic scores, a migrant dummy and (within 5^{th} grade) gender-specific rank. Class controls include (leave-one-out) the share of girls, the (leave-one-out) share of migrants, the (leave-one-out) average socio-economic score, the (leave-one-out) gender-specific average math score, and the 5^{th} grade class size. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the 5^{th} grade school level and at the 8^{th} grade class level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table A2: Heterogeneous effects on 8^{th} grade math scores by quartiles of the 5^{th} grade math scores distribution

VARIABLES	(1) 8^{th} grade math score
Share of top girls in math in 5^{th} grade	-0.0090***
	(0.0032)
Share of top girls in math in 5^{th} grade × Girl	0.0429***
	(0.0038)
Share of top boys in math in 5^{th} grade	0.0266***
	(0.0033)
Share of top boys in math in 5^{th} grade × Girl	-0.0440***
	(0.0038)
Q1	-0.1104***
	(0.0084)
Q4	0.1119***
	(0.0087)
Girl dummy × Q1	0.0117**
	(0.0059)
Girl dummy × Q4	-0.0895***
	(0.0059)
Share of top girls in math in 5^{th} grade × Q1	0.0006
	(0.0049)
Share of top girls in math in 5^{th} grade × Girl × Q1	-0.0204***
	(0.0065)
Share of top boys in math in 5^{th} grade × Q1	-0.0186***
	(0.0054)
Share of top boys in math in 5^{th} grade × Girl × Q1	0.0188***
	(0.0065)
Share of top girls in math in 5^{th} grade × Q4	-0.0170***
	(0.0048)
Share of top girls in math in 5^{th} grade × Girl × Q4	0.0008
	(0.0066)
Share of top boys in math in 5^{th} grade × Q4	-0.0108**
	(0.0048)
Share of top boys in math in 5^{th} grade × Girl × Q4	0.0043
	(0.0064)
Observations	351,277
R-squared	0.6181
Primary school FE	YES
8^{th} grade class FE	YES
Individual controls	YES
Class controls	YES
Coeff: share of top girls (1 + below 25)	-0.00834
F-test: share of top girls (1 + below 25)	3.522
$P > F$: share of top girls (1 + below 25)	0.0606
Coeff: share of top girls (1 + above 75)	-0.0260
F-test: share of top girls (1 + above 75)	35.41
$P > F$: share of top girls (1 + above 75)	2.84e-09
Coeff: share of top girls (1 + girl)	0.0339
F-test: share of top girls (1 + girl)	110
$P > F$: share of top girls (1 + girl)	0
Coeff: share of top girls (1 + girl + below 25 + girl × below 25)	0.0141
F-test: share of top girls (1 + girl + below 25 + girl × below 25)	9.386
$P > F$: share of top girls (1 + girl + below 25 + girl × below 25)	0.00220
Coeff: share of top girls (1 + girl + above 75 + girl × above 75)	0.0177
F-test: share of top girls (1 + girl + above 75 + girl × above 75)	14.61
$P > F$: share of top girls (1 + girl + above 75 + girl × below 25)	0.000134
Coeff: share of top boys (1 + below 25)	0.00804
F-test: share of top boys (1 + below 25)	2.776
$P > F$: share of top boys (1 + below 25)	0.0958
Coeff: share of top boys (1 + above 75)	0.0159
F-test: share of top boys (1 + above 75)	13.61
$P > F$: share of top boys (1 + above 75)	0.000227
Coeff: share of top boys (1 + girl)	-0.0174
F-test: share of top boys (1 + girl)	32.28
$P > F$: share of top boys (1 + girl)	1.40e-08
Coeff: share of top boys (1 + girl + below 25 + girl × below 25)	-0.0171
F-test: share of top boys (1 + girl + below 25 + girl × below 25)	17.77
$P > F$: share of top boys (1 + girl + below 25 + girl × below 25)	2.54e-05
Coeff: share of top boys (1 + girl + above 75 + girl × above 75)	-0.0238
F-test: share of top boys (1 + girl + above 75 + girl × above 75)	26
$P > F$: share of top boys (1 + girl + above 75 + girl × above 75)	3.53e-07

Note: Individual controls include fixed effects for each decile of the distribution of 5^{th} grade math scores, fixed effects for each decile of the distribution of socio-economic scores, a migrant dummy and (within 5^{th} grade) gender-specific rank. Class controls include (leave-one-out) the share of girls, the (leave-one-out) share of migrants, the (leave-one-out) average socio-economic score, the (leave-one-out) gender-specific average math score, and the 5^{th} grade class size. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the 5^{th} grade school level and at the 8^{th} grade class level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table A3: Heterogeneous effects on the probability to choose *Liceo Scientifico* on kids with/without high achievers in 8^{th} grade

VARIABLES	(1) Liceo scientifico
Share of top girls in math in 5^{th} grade	-0.0060**
	(0.0023)
Share of top girls in math in 5^{th} grade × Girl	0.0057*
	(0.0031)
Share of top boys in math in 5^{th} grade	0.0091***
	(0.0025)
Share of top boys in math in 5^{th} grade × Girl	-0.0163***
	(0.0031)
With at least one high achieving in 8^{th} grade (except oneself)	-0.0024
	(0.0029)
Girl dummy × At least one HAP	0.0106***
	(0.0036)
Share of top girls in math in 5^{th} grade × At least one HAP	-0.0004
	(0.0029)
Share of top girls in math in 5^{th} grade × Girl × At least one	0.0082**
	(0.0039)
Share of top boys in math in 5^{th} grade × At least one HAP	0.0080**
	(0.0032)
Share of top boys in math in 5^{th} grade × Girl × At least one	-0.0100**
	(0.0040)
Observations	289,960
R-squared	0.2752
Primary school FE	YES
8^{th} grade class FE	YES
Individual controls	YES
Class controls	YES
Coeff: share of top girls (1 + girl)	-0.000310
F-test: share of top girls (1 + girl)	0.0173
$P > F$: share of top girls (1 + girl)	0.896
Coeff: share of top girls (1 + SC)	-0.00634
F-test: share of top girls (1 + SC)	8.682
$P > F$: share of top girls (1 + SC)	0.00323
Coeff: share of top girls (1 + girl + SC + girl × SC)	0.00750
F-test: share of top girls (1 + girl + SC + girl × SC)	11.95
$P > F$: share of top girls (1 + girl + SC + girl × SC)	0.000552
Coeff: share of top boys (1 + girl)	-0.00715
F-test: share of top boys (1 + girl)	10.80
$P > F$: share of top boys (1 + girl)	0.00102
Coeff: share of top boys (1 + SC)	0.0172
F-test: share of top boys (1 + SC)	57.42
$P > F$: share of top boys (1 + SC)	0
Coeff: share of top boys (1 + girl + SC + girl × SC)	-0.00917
F-test: share of top boys (1 + girl + SC + girl × SC)	19.69
$P > F$: share of top boys (1 + girl + SC + girl × SC)	9.28e-06

Note: Individual controls include fixed effects for each decile of the distribution of 5^{th} grade math scores, fixed effects for each decile of the distribution of socio-economic scores, a migrant dummy and (within 5^{th} grade) gender-specific rank. Class controls include (leave-one-out) the share of girls, the (leave-one-out) share of migrants, the (leave-one-out) average socio-economic score, the (leave-one-out) gender-specific average math score, and the 5^{th} grade class size. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the 5^{th} grade school level and at the 8^{th} grade class level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table A4: Heterogeneous effects on the probability to choose *Liceo Scientifico* by quartiles of the 5^{th} grade math scores distribution

VARIABLES	(1) Liceo scientifico
Share of top girls in math in 5^{th} grade	-0.0043**
	(0.0021)
Share of top girls in math in 5^{th} grade × Girl	0.0125***
	(0.0027)
Share of top boys in math in 5^{th} grade	0.0151***
	(0.0022)
Share of top boys in math in 5^{th} grade × Girl	-0.0233***
	(0.0026)
Q1	-0.0405***
	(0.0052)
Q4	0.0385***
	(0.0063)
Girl dummy × Q1	0.0366***
	(0.0036)
Girl dummy × Q4	-0.0457***
	(0.0042)
Share of top girls in math in 5^{th} grade × Q1	0.0027
	(0.0030)
Share of top girls in math in 5^{th} grade × Girl × Q1	-0.0058
	(0.0040)
Share of top boys in math in 5^{th} grade × Q1	-0.0112***
	(0.0033)
Share of top boys in math in 5^{th} grade × Girl × Q1	0.0128***
	(0.0040)
Share of top girls in math in 5^{th} grade × Q4	-0.0090***
	(0.0032)
Share of top girls in math in 5^{th} grade × Girl × Q4	0.0048
	(0.0046)
Share of top boys in math in 5^{th} grade × Q4	-0.0020
	(0.0033)
Share of top boys in math in 5^{th} grade × Girl × Q4	-0.0008
	(0.0045)
Observations	289,960
R-squared	0.2762
Primary school FE	YES
8^{th} grade class FE	YES
Individual controls	YES
Class controls	YES
Coeff: share of top girls (1 + below 25)	-0.00162
F-test: share of top girls (1 + below 25)	0.369
$P > F$: share of top girls (1 + below 25)	0.544
Coeff: share of top girls (1 + above 75)	-0.0133
F-test: share of top girls (1 + above 75)	21.88
$P > F$: share of top girls (1 + above 75)	2.97e-06
Coeff: share of top girls (1 + girl)	0.00813
F-test: share of top girls (1 + girl)	14.59
$P > F$: share of top girls (1 + girl)	0.000135
Coeff: share of top girls (1 + girl + below 25 + girl × below 25)	0.00502
F-test: share of top girls (1 + girl + below 25 + girl × below 25)	4.068
$P > F$: share of top girls (1 + girl + below 25 + girl × below 25)	0.0437
Coeff: share of top girls (1 + girl + above 75 + girl × above 75)	0.00394
F-test: share of top girls (1 + girl + above 75 + girl × above 75)	1.685
$P > F$: share of top girls (1 + girl + above 75 + girl × below 25)	0.194
Coeff: share of top boys (1 + below 25)	0.00393
F-test: share of top boys (1 + below 25)	1.865
$P > F$: share of top boys (1 + below 25)	0.172
Coeff: share of top boys (1 + above 75)	0.0131
F-test: share of top boys (1 + above 75)	21.84
$P > F$: share of top boys (1 + above 75)	3.03e-06
Coeff: share of top boys (1 + girl)	-0.00814
F-test: share of top boys (1 + girl)	17.73
$P > F$: share of top boys (1 + girl)	2.59e-05
Coeff: share of top boys (1 + girl + below 25 + girl × below 25)	-0.00652
F-test: share of top boys (1 + girl + below 25 + girl × below 25)	9.333
$P > F$: share of top boys (1 + girl + below 25 + girl × below 25)	0.00226
Coeff: share of top boys (1 + girl + above 75 + girl × above 75)	-0.0109
F-test: share of top boys (1 + girl + above 75 + girl × above 75)	12.80
$P > F$: share of top boys (1 + girl + above 75 + girl × above 75)	0.000349

Note: Individual controls include fixed effects for each decile of the distribution of 5^{th} grade math scores, fixed effects for each decile of the distribution of socio-economic scores, a migrant dummy and (within 5^{th} grade) gender-specific rank. Class controls include (leave-one-out) the share of girls, the (leave-one-out) share of migrants, the (leave-one-out) average socio-economic score, the (leave-one-out) gender-specific average math score, and the 5^{th} grade class size. All variables (except dummies) are demeaned and expressed in units of standard deviations. Standard errors are clustered at the 5^{th} grade school level and at the 8^{th} grade class level. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.