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Comparative Advantage and Gender Gap in STEM

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ABSTRACT

Why are females, compared with males, both more likely to have strong STEM-related performance and less likely to enter a STEM field later on? We exploit random classroom assignment to identify the impact of comparative STEM advantage on specialization decisions. Comparative STEM advantage is proxied by the within-classroom ranking of the ratio of STEM over non-STEM performance. We find that females with a higher comparative STEM advantage are more likely to choose a STEM school track and apply for a STEM degree. Comparative STEM advantage explains 12% of the underrepresentation of qualified females in the earliest instance of STEM specialization.

Keywords: gender gap, STEM, random peer effects, ordinal rank, absolute advantage, comparative advantage

JEL Classification: I21, I24, J24

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1 Introduction

It is well established that males are more likely than females to take mathematically oriented courses in school and obtain bachelor's degrees in computer sciences, engineering, physical sciences, and mathematics disciplines (National Science Foundation, 2016, 2017). Is this because females perform poorly in mathematics and physics in school? The answer is no. Although gender gaps in STEM university enrollment persist, the underperformance of women on mathematics and physics tests has narrowed or even reversed in many countries. According to a recent OECD report on PISA scores, in Iceland, Sweden, Norway, Finland, Israel, Indonesia, and Greece the gender gap in mathematics and science has reversed in favor of females (OECD, 2016).[1] Thus, females' low performance in STEM does not fully explain the underrepresentation of women in STEM disciplines (Ceci et al., 2014).

There is still debate regarding what shapes gender differences in field and occupation specialization. Previous studies highlight the roles of biological, social, psychological, and environmental factors that might influence this gap (Benbow, 1988; Waber, 1976; Steele, 1997; Lavy and Megalokonomou, 2019). In addition to those factors, students may also be likely to base course enrollment and degree specialization decisions on their beliefs about their relative academic abilities (Eccles, 1983; Wang and Degol, 2013; Stoet and Geary, 2018; Breda and Napp, 2019). In this paper, we investigate how the relative comparison of a student's own academic strengths and weaknesses with respect to her classmates affects her decision to select and specialize in a STEM field.

To examine this, we introduce the concepts of absolute and comparative advantage among one's classroom peers and consider their role in field specialization decisions. We take two groups of subjects that lead to different university degree programs and occupations: STEM and non-STEM.[2] Students allocate their time between studying for those two types of subjects, which require different skills. Non-STEM subjects mainly rely on reading, writing, and comprehension skills, while STEM subjects mainly rely on analytical skills. Students might make different time investment and specialization decisions depending on their relative performance in one group of subjects compared with another.

[1]For more information, see `https://data.oecd.org/pisa/mathematics-performance-pisa.htm`.

[2]This distinction is of high interest, since there is underrepresentation of females in STEM-related majors, faculties, and occupations. This has important consequences for women, as well as for the entire society. Indeed, STEM occupations generally pay a higher salary; therefore, the lack of women working on these occupations contributes to the widening of the gender wage gap (Beede et al., 2011; Sloane et al., 2019; Duflo, 2012; Black et al., 2008; Blau and Kahn, 2017). Moreover, improved gender diversity in the workplace has been identified as an important driver for the development of new technology and innovations (Hong and Page, 2001; Clayton and Collins, 2014).

We first investigate whether there exists a gender performance gap in these two types of compulsory subjects, STEM and non-STEM, then construct a measure of *absolute STEM advantage*. We define absolute STEM advantage as the ratio between a student's average performance in STEM and non-STEM subjects. This measure conceptualizes a student's assessment of her own academic strengths in one group (i.e., STEM) relative to the other group of subjects (i.e., non-STEM). Then, we construct a measure of *comparative STEM advantage*, which reflects how a student's absolute STEM advantage compares with that of her randomly assigned classmates. We approximate comparative STEM advantage using the within-classroom rank of students' absolute STEM advantage in 10^{th} grade. We develop a simple theoretical model to provide insights on why absolute and comparative STEM advantage may affect students' specialization decision.

In our context, students choose a specialization track at the end of the 10^{th} grade. This is the first opportunity students have to specialize in a field during their school career. We observe students' STEM specialization decision in this instance. We also consider students end-of-high school STEM specialization outcomes by looking at their university degree applications. In this paper, we ask the following question: What is the causal effect of comparative STEM advantage, measured early in high school, on the longer-term likelihood of STEM specialization for males and females? To answer this question, we use new data for more than 70,000 students from a sample of 123 public high schools in Greece. We exploit an institutional setting in which students at the beginning of high school (10^{th} grade) are quasi-randomly (alphabetically based on surname) assigned to classrooms. Students stay with the same classmates for all courses for the whole school year. We rely on the assumption that people naturally make comparisons with others within their peer group (Festinger, 1954) using ordinal rank (Tincani, 2017; Bursztyn and Jensen, 2015). We believe that students have a decent understanding of their relative standing within their classroom, based on repeated interactions with classmates and teachers.

To illustrate our identification strategy, consider two students with the same average performance in STEM and non-STEM, and thus the same absolute STEM advantage. The first student is assigned to a classroom in which all peers have a lower absolute STEM advantage compared with her. Therefore, this student ranks at the top of her classroom in terms of her absolute STEM advantage. The second student is assigned to a classroom (same average classroom characteristics and inputs as the other classroom) in which *two* peers have a higher absolute STEM advantage compared with her. Therefore, she ranks third in terms of absolute STEM advantage within her classroom. Our basic idea is to compare the specialization outcomes of pupils who have the same characteristics and the same raw performance, who are—by chance—in groups in which they have a different relative standing in absolute STEM advantage, due to practically random peer group formation. It is important to stress that our identification strategy exploits variation in the *dispersion* of absolute STEM advantage within classrooms of the same average characteristics and inputs. This idiosyncratic variation arises because of small class size.

Our findings can be summarized as follows. First, we confirm evidence in the literature on two points: (1) females outperform males in both STEM and non-STEM subjects[3] and (2) females score much higher than males in non-STEM subjects than they do in STEM subjects. We also find that females have a lower comparative STEM advantage among quasi-random classmates than males. Second, we exploit random variation in a student's relative standing within her classroom to study the impact of comparative STEM advantage on future specialization decisions. We find that an increase in comparative STEM advantage by two positions within the classroom,[4] leads to an increase in the likelihood of enrolling in a STEM track by 1.9 percentage points for females. The effect is much smaller or not statistically different from zero for males. Our findings suggest that between 4 and 6 percentage points of the 34-percentage-point gender gap (or 12-18%) in initial STEM specialization in high school is attributable to the influence of comparative STEM advantage.

Our findings show that comparative STEM advantage has longer term implications. In particular, we show that one's comparative STEM advantage in grade 10 has implications on students' preferences 2 years later, when they apply to university degree programs. Specifically, we find that assignment to a classroom that increases a student's comparative STEM advantage by 10% increases her likelihood of applying for a STEM degree at the university by around 1% for females, while males are not affected. We also find a significant effect of comparative STEM advantage on STEM performance in grades 11 and 12. We find similar results when the comparative STEM advantage is computed with respect to same-gender classmates, and weaker effects when it is computed with respect to school-cohort peers. Our results highlight the role of comparative STEM advantage in the underrepresentation of females in STEM disciplines.

We conduct a series of robustness exercises to further support our identification strategy. First, we show that results remain similar when we use different functional forms of absolute STEM advantage. Our preferred specification includes a flexible nonlinear functional form for absolute STEM advantage, but the results are similar when a linear, quadratic, cubic, quartic, or quintic functional form is used. Second, we show that students at different parts of the comparative STEM advantage distribution do not have different attrition behavior. Our results remain similar when

[3]This finding has been established through meta-analysis (O'Dea et al., 2018).

[4]This is equivalent to a 10% increase in comparative STEM advantage.

we account for attrition weights in the main specification (inverse attrition weights). Third, we use student performance measured at different times and find that our results remain qualitatively unaffected. Fourth, we show that our results are robust when we use a different STEM definitions for subjects and degree programs.

Our study moves beyond previous studies in several important ways. First, we contribute to the literature of field specialization decisions in education. To our knowledge, we are the first to incorporate the concepts of absolute *and* comparative advantage in the classroom and causally address the latter. In other words, we put together two dimensions of comparison: the within-individual comparison of different sets of skills and the social comparison of those with others. These factors help us explain what drives students into different specializations. The within individual comparison of one's relative strengths and weaknesses refers to absolute STEM advantage.[5] The second dimension of comparison refers to one's strengths in different fields *relative* to the strengths of others around them. According to Tversky and Kahneman (1974) individuals adopt cognitive short-cuts, such as the use of ordinal information, when they compare themselves with others. Therefore, we proxy one's comparative advantage in one group of subjects compared with the other by using the rank in STEM relative to non-STEM performance within the classroom. The research designs used in recent studies do not incorporate within-individual skill comparison (Elsner and Isphording, 2017; Murphy and Weinhardt, 2018; Elsner et al., 2018; Delaney and Devereux, 2019).

Second, we contribute to the identification of rank. While previous studies exploit non-random variation in cohort composition within schools (Elsner and Isphording, 2017; Murphy and Weinhardt, 2018; Delaney and Devereux, 2019), we exploit within-school-cohort idiosyncratic variation in *classrooms'* ability composition. While the former cannot exclude the possibility of confounding school-cohort shocks, we are able to control for this unobserved endogeneity in our identification. In other words, we exploit the random variation of students' abilities in classrooms within the same cohort and school, to account for cohort selection bias. The ideal research design for disentangling the effects of within-individual and across-individual comparisons would require that identical students be randomly assigned to peer groups. Those peer groups would need to have the same group characteristics, but different ability distributions, which would result in students placing themselves in different ranked positions in their peer group distribution. The alphabetical assignment

[5] Some biological explanations have been proposed regarding the higher performance of males in STEM compared with non-STEM subjects in some countries, and their higher propensity to enroll in STEM related disciplines. The main research in this area includes analysis of diversity in brain composition (Gur et al., 1999; De Bellis et al., 2001; Cahill, 2005; Gallagher and Kaufman, 2005), males' greater spatial orientation due to evolutionary foundation (Gaulin et al., 1988); or the influence of more complex environments (Berenbaum et al., 2008).

of students to peer groups we exploit in this paper resembles the ideal quasi-experiment.

Our study's third contribution relates to the broad external validity of our findings. This is the first study to examine explores social comparisons using the full support of the ability distribution. Unlike Elsner et al. (2018), who explore social comparisons at a Dutch business school, our results draw on a broader range of the ability distribution. We consider students before they specialize in a given field for the first time in their school careers. Understanding the impact of social comparisons at first instance of student specialization may be of particular policy relevance.

We also contribute to the literature on the longer-term effects of rank in education, by looking at longer-term STEM study decisions. In particular, we provide evidence that students' comparative advantage in STEM in grade 10 affects not only their STEM specialization decision in grade 11, but also their decision to apply to a 4- or 5-year STEM university degree program. Our study helps explain why females choose to specialize in non-STEM disciplines, which are associated with lower wages, even though they outperform males in both STEM and non-STEM subjects.

Finally, we contribute to the literature of gender differences in responsiveness to grade information. Owen (2010) finds that females are more likely to use grades as feedback about their ability to a higher extent than males. Females may perceive lower grades as confirmation of stereotypes by which females are not as good as males in STEM subjects.[6] Our findings highlight not only that females may be more sensitive to grades than males, but also that females may be more attentive to their ordinal comparison within their group of reference than males.

2 A Simple Model of STEM Specialization

In this section, we develop a simple theoretical framework to motivate why comparative STEM advantage may affect STEM specialization. This theoretical framework explores the channels through which the comparison of academic strengths in different fields both within the same individual and between individuals may influence a student's STEM specialization decision. The goal of this framework is not to motivate an empirical strategy but to highlight the key conditions under which comparative STEM advantage may have a distinct influence on STEM study.

The idea that individuals with heterogeneous skill levels may compare their own skills with those of other individuals is not new in the literature. In the seminal Roy-Borjas model of self-selection

[6] A study in psychology corroborates the idea that female students are more likely than male students to attribute negative feedback to their own low ability (Dweck et al., 1978). Also, Rask and Tiefenthaler (2008) show that women have greater grade reliance, especially with respect to STEM-related subjects, and negative feedback may serve to bolster and confirm their negative stereotypes. Steele (1997) examines how women in quantitative fields encounter stereotype threats that challenge their ability to identify themselves within those fields.

(Roy, 1951; Borjas, 1987), specialization decisions are shown to rely heavily on the distribution of skills and abilities within and across individuals. Eccles's (1983) expectancy value theory, supported by empirical evidence from the US (Wang et al., 2013; Gardner, 2016), suggests that students use their own relative performance to evaluate their academic strengths and subsequently make STEM-related enrollment decisions. At the same time, Zafar (2011) and Bobba and Frisancho (2016) identify social comparison as a crucial driver for enrollment decisions in different fields of study. Exploring the theoretical underpinnings of the STEM specialization decision allows us to deduce the conditions under which the social comparison of different skills might lead to underrepresentation of qualified individuals in occupations associated with those skills.

Suppose there are many individuals $i \in I$ who interact in a peer environment. Each individual chooses a specialization that maximizes her utility. Each specialization leads to an occupation that employs the skills intensively related to this specialization. There are only two specializations: STEM (which would lead to occupations such as engineer) and non-STEM (which would lead to occupations such as lawyer). The utility function of individual i specializing in k (STEM or non-STEM) is an increasing function of monetary returns, w_i^k, and nonmonetary returns, p_i^k, which may allow for substitution. For exposition, we assume the following multiplicative utility function without loss of generality:

$$U_i^k = f(p_i^k, w_i^k) = p_i^k \cdot w_i^k \quad \text{where } k = \{S, NS\}$$

so that $\frac{\partial U_i^k}{\partial p_i^k} > 0$, $\frac{\partial U_i^k}{\partial w_i^k} > 0$. Suppose the nonmonetary return, associated with idiosyncratic preference for specialization k, takes a scalar form. The nonmonetary return, p_i^k, represents individual i's preference for specialization k, which could reflect, inter alia, nonpecuniary aspects of the occupation associated with specialization k. Suppose also that the monetary return to specialization k, associated with earnings from labor in a k-related occupation, is an increasing function of individual i's own competence in k, α_i^k, and a decreasing function of the competence of every other individual in k, α_{-i}^k, where -$i \in I$-$\{i\}$,[7] as follows:

$$w_i^k = f(\alpha_i^k, \alpha_{-i}^k) \quad \text{where } \alpha_i^k, \alpha_{-i}^k > 0$$

so that $\frac{\partial w_i^k}{\partial \alpha_i^k} > 0$, $\frac{\partial w_i^k}{\partial \alpha_{-i}^k} < 0$ and $\frac{\partial^2 w_i^k}{\partial \alpha_i^k \delta \alpha_{-i}^k} < 0$. The key assumption of our theoretical framework is that an individual's expected earnings in a k-related occupation is proportional to her competence

[7]We think of -i as a series of all contenders of i. Thus, α_{-i}^k may be thought of as a vector with every contender's competence in k.

in k relative to the competence of others in the same discipline.[8] For simplicity, assume that each individual is small enough compared with the labor market, so that their decision to follow a k specialization and consequently a k-related occupation, will not influence market competence α_{-i}^k or market wage w^k. For exposition, suppose a multiplicative monetary return function of the following form:

$$w_i^k = \lambda^k \left(\frac{\alpha_i^k}{\alpha_{-i}^k}\right)$$

where λ^k denotes the marginal expected return to relative competence in discipline k. Individual i would specialize in STEM if and only if:

$$U_i^S > U_i^{NS}$$

$$\Leftrightarrow p_i^S \cdot \lambda^S \left(\frac{\alpha_i^S}{\alpha_{-i}^S}\right) > p_i^{NS} \cdot \lambda^{NS} \left(\frac{\alpha_i^{NS}}{\alpha_{-i}^{NS}}\right)$$

$$\Leftrightarrow \frac{\frac{\alpha_i^S}{\alpha_i^{NS}}}{\frac{\alpha_{-i}^S}{\alpha_{-i}^{NS}}} > \frac{p_i^{NS} \cdot \lambda^{NS}}{p_i^S \cdot \lambda^S} \tag{1}$$

where $\frac{\alpha_i^S}{\alpha_i^{NS}}$ represents student i's own absolute advantage in STEM and $\frac{\alpha_{-i}^S}{\alpha_{-i}^{NS}}$ represents the absolute STEM advantage of others student i competes with. The LHS of decision rule (1) is a cardinal measure of comparative STEM advantage. In the case of a school or classroom environment, student i is likely to compete with her school or classroom peers, respectively. Thus, a student is likely to compare her absolute STEM advantage to the absolute STEM advantage of each of her school or classroom peers. If we assume for simplicity that $p_{NS} \cdot \lambda^{NS} = p_S \cdot \lambda^S$, then decision rule (1) becomes $\frac{\alpha_i^S}{\alpha_i^{NS}} > \frac{\alpha_{-i}^S}{\alpha_{-i}^{NS}}$, suggesting that an individual chooses to specialize in STEM only when her strength in STEM relative to non-STEM exceeds her peer's strengths in STEM relative to non-STEM.

Naturally, students may not know the α's of every other person in the general student population, and thus may not know how their own academic strengths compare with those of everyone else. Students may instead use a proxy to estimate how their strengths compare with the strengths of their *classroom peers* because they interact with them for a considerable part of the day.

The intuition drawn from our theoretical discussion can motivate the following hypothesis related to STEM specialization and be tested empirically: The higher an individual's relative

[8] This assumption is not too heroic. Consider the sorting algorithm based on which students gain admission to tertiary education. Consider also that more competitive STEM (non-STEM) degrees may be associated with higher expected earnings than less competitive STEM (non-STEM) degree programs.

standing among her contenders in terms of comparative STEM advantage, the more likely she is to specialize in STEM, ceteris paribus. We investigate this hypothesis in Section 4.

3 Data and Institutional Framework

In this section, we describe the data and institutional setting of school and classroom assignment. We also describe the processes of track specialization in high school and college application in Greece. We conducted a secondary data collection by visiting and retrieving administrative data from a sample of 123 public schools[9] and more than 70,000 students. Our school sample corresponds to roughly 10% of public schools in Greece.

Each student record contains an individual identifier, a school and classroom identifier, and detailed demographic information on the student: year of birth, gender, a complete track enrollment history, high-school graduation status, high-school graduation year, and test scores for each student in each subject and grade. We have information for all high school grades, namely 10^{th}, 11^{th}, and 12^{th} grades. The panel data span from 2001 to 2009. We also obtained access to administrative records collected by the Hellenic Ministry of Education. For each university applicant, we have information on the degrees they applied for. We link each student's file with administrative records that include postsecondary application information.

The educational system in Greece is highly centralized (OECD, 2018). Students are assigned to public schools through zoning based on their residential address and geographic proximity to a school.[10] Once students enroll in a given high school, they are assigned to a physical classroom where they take all courses. The assignment of students and teachers to classrooms within each school is random.[11] In particular, in accordance with a law that is strictly enforced, students are allocated to classrooms in an alphabetical order based on their surname. Students are not allowed to switch classrooms. This alphabetical classroom assignment allows for a randomization of peer characteristics in the classroom, which we show later.

We identify three subjects as STEM-related: Algebra, Physics and Chemistry; and three subjects as non-STEM-related: Modern Greek, Greek Literature, and Ancient Greek. These six subjects are compulsory and taken by all students from grade 10 to grade 12. We approximate the concept of individual competence in STEM relative to non-STEM, presented in Section 2, using

[9] Using data from the same environment, we have shown that the sample is nationally representative with regard to several important variables, such as female share and track choice (Goulas and Megalokonomou, 2015).

[10] Families are unable to enroll their children in a different public school than the one assigned, since they are required to provide proof of their residential address and utility bills.

[11] Evidence of this random assignment in the same context can be found in Lavy and Megalokonomou (2019).

the ratio between average scores in STEM over non-STEM subjects for each student. Thus, we define absolute STEM advantage[12] as follows:

$$\text{Student } i\text{'s Absolute STEM Advantage} = \frac{\text{Student i's Av. score in STEM subjects}}{\text{Student i's Av. score in non-STEM subjects}} \quad (2)$$

In the first instance, students have to choose a specialization track between the end of the 10^{th} and the beginning of the 11^{th} grade. The available tracks are Classics, Science, and Information Technology. Each track requires that students take different sets of courses in order to graduate. Students may choose to remain in the same track or change tracks between the end of the 11^{th} and the beginning of the 12^{th} grade.[13] Figure 1 shows the timeline of the choices high school students face. We categorize the Classics track as a non-STEM track, and Science and Information Technology tracks as STEM tracks. There is no minimum performance threshold for students to enroll in any track, and all schools offer exactly three tracks. Each track has different compulsory subjects. At the end of each year, all students take final exams in the courses they took during the same academic year.[14] We use 10^{th} grade performance on final exams to compute our main variables.[15]

University admission is centralized and administered by the Ministry of Education. To apply for a university degree program, students must take standardized national exams at the end of the 12^{th} grade. After taking these exams, applicants submit a list of their preferred tertiary degree programs[16] to the Ministry of Education (OECD, 2018).

We consider two educational outcomes: STEM track choice in grade 11 and application to a university STEM degree program. We consider all degree programs offered by Science, Engineering, and Technology departments to be STEM degree programs. Health sciences, such as Medicine and Biology are not considered STEM, nor are Business and Economics.[17] The two outcomes variables are nested, in the sense that only students who attended a STEM track in the 12^{th} grade can apply to a STEM degree program.[18] Finally, we look at the average performance in STEM subjects in

[12]We discuss the association between absolute STEM advantage and future study decision in the Appendix.

[13]Only 0.7% of students in our sample move to a different track after the end of grade 11.

[14]Students must demonstrate sufficient performance on their final exams to progress to the next grade.

[15]In Section 5.1.5, we show that our result are robust when we use performance in the first semester instead of final exam performance in 10^{th} grade.

[16]By "degree program," we mean a department at a specific university. Each university department offers exactly one bachelor's degree program (*ptychion*).

[17]In Table A7 we show that our main results are robust to the inclusion of Health Science, Business, and Economics in the definition of STEM departments.

[18]Students in the Classics track may apply to a STEM degree program by incurring a penalty (in the form of a reduction of their test scores) and only if they take national exams in the STEM courses. This scenario corresponds to a negligible share of university applicants coming from the Classics track in high school. Our analysis of applications for a STEM degree programs only considers candidates from a STEM high school track, for

grades 11 and 12, as an outcome.

3.1 Descriptive Statistics

Panel A of Table 1 shows average performance by gender and subject. Females perform, on average, significantly better than males in almost every subject. We plot those performance differences by gender in Figure 2. We show that females outperform males much more in non-STEM than in STEM subjects.[19] Panel B in Table 1 shows that females' overperformance is even higher in non-STEM (=1.594) compared with STEM (=0.349). Class-level differences for males and females are not statistically different from zero, indicating that class randomization has been indeed successful. Combining these, females have a lower comparative advantage in STEM subjects compared with males (0.409 for females and 0.487 for males). Panel C shows that despite females' overperformance in both STEM and non-STEM subjects, they are 34% less likely to choose a STEM track at the end of grade 10, and 6.2% less likely to apply to a STEM university department, conditional on enrolling in a STEM track in 12$^{\text{th}}$ grade.[20]

Figure A3 shows the shares of females and males by quintile of performance in STEM and non-STEM subjects. The top figure shows that 55% are females across all quintiles of STEM performance, including the top quintile (5$^{\text{th}}$ quintile). The bottom figure shows that in the top quintile of non-STEM performance, the proportion of females (75%) is much higher than males (25%). Table A1 shows summary statistics for STEM specialization by gender. Differences in comparative STEM advantage for individuals who specialize in STEM compared with those who specialize in non-STEM are larger for males than females.[21]

4 The Effect of Comparative STEM Advantage

In this section, we empirically examine the relationship between a student's comparative STEM advantage and her likelihood of specializing in STEM, ceteris paribus. In other words, we attempt to tease out the distinct role of comparative STEM advantage in future STEM specialization outcomes, while controlling for absolute STEM advantage.

whom the cost of applying to a STEM degree program is homogeneous.

[19]Figure A1 shows the performance distributions for males and females in STEM (top figure) and non-STEM subjects (bottom figure).

[20]Figure A2 shows that the distribution of absolute STEM advantage is shifted to the left for females compared with males.

[21]We discuss Table A1 in the Appendix.

Estimating the effect of comparative STEM advantage, in addition to absolute STEM advantage, on future STEM specialization is challenging for several reasons. First, these absolute and comparative STEM advantages are correlated by construction, which renders the identification of their distinct effects difficult. This could introduce issues with the reliability and precision of the estimates. At the same time, both absolute and comparative STEM advantage may be correlated with student unobservable characteristics (e.g., preferences or motivation), which may also influence student specialization decisions. This could potentially introduce bias due to omitted unobservable confounders in the effect of interest. We mitigate both of these problems by employing an ordinal, rather than cardinal, measure of comparative STEM advantage, while controlling for absolute STEM advantage. Specifically, we approximate comparative STEM advantage using the within-classroom rank of absolute STEM advantage.[22]

Using rank of absolute STEM advantage to approximate comparative STEM advantage has several benefits. First, in the heuristic process of comparison, individuals end up transforming complex assessments into manageable subjective tasks by employing cognitive short-cuts, such as "How do I rank relative to my group?" (Tversky and Kahneman, 1974). Therefore, the rank in absolute STEM advantage represents an easier instrument students use for social comparison. Second, the economics literature documents the distinct role of rank-ordered positions in several outcomes (Brown et al., 2008; Card et al., 2012; Murphy and Weinhardt, 2018). Third, using rank allows us to investigate the causal effect of comparative advantage on later choices and investments. In our setting, individuals have control over their own absolute STEM advantage, but they cannot fully influence their relative assessment or rank, since assignment to a peer group is random. Therefore, we are able to isolate the causal effect of comparative STEM advantage, in addition to the influence of absolute STEM advantage.

4.1 Defining Comparative STEM Advantage

We define each student's comparative STEM advantage as her within-classroom percentile rank of absolute STEM advantage in grade 10, defined in equation (2), as follows:

$$\text{Comparative STEM advantage} = \frac{\text{Ordinal Rank of Absolute STEM Advantage} - 1}{\text{Classroom Size} - 1} \tag{3}$$

[22] An alternative approach would be to approximate comparative STEM advantage using the ratio of a student's absolute STEM advantage to her classroom's absolute STEM advantage. While the ratio on the LHS of decision rule (1) is a cardinal measure of comparative STEM advantage, the rank in STEM advantage is an ordinal measure of comparative advantage in STEM within the classroom. We explore this approach in Table A3.

We first compute the ordinal rank of absolute STEM advantage for each student. This number goes from 1 to N, where N is each classroom's size. The student with the highest absolute STEM advantage in the classroom is given an ordinal rank value equal to NN The student with the lowest absolute STEM advantage in the classroom is assigned a value of 1. In order to obtain a comparable measure of rank across classrooms, we transform each student's ordinal rank to a percentile rank, as in equation (3). We use this percentile rank as a measure of comparative STEM advantage and thus it is bounded between 0 and 1. The student with the highest absolute STEM advantage within her classroom has a comparative STEM advantage of 1, while the student with the lowest absolute STEM advantage has a comparative STEM advantage of 0.[23]

Figure 3 shows sizeable variation in comparative STEM advantage with respect to different levels of absolute STEM advantage. A student with an absolute STEM advantage equal to 0.4 is likely to be have one of the lowest comparative STEM advantage values in her classroom. A student with an absolute STEM advantage of 1.4 is likely to have one of the highest comparative STEM advantage values in her classroom. A student with an absolute STEM advantage of 0.8 may have almost any comparative STEM advantage value, depending on which classroom she is assigned to.[24] Figure 4 shows the distribution of comparative STEM advantage values for males and females. Males are more likely than females to have a higher comparative STEM advantage.

4.2 Identifying Variation

We exploit quasi-random variation in classroom composition within schools and cohorts that arises from the alphabetical assignment of students to classrooms. This random assignment of students to classrooms within school-cohorts produces exogenous variation in comparative STEM advantage, for a given absolute STEM advantage. In other words, our identification strategy compares students with the same performance in STEM and non-STEM subjects, and therefore the same absolute STEM advantage. These students may have different *rankings* in absolute STEM advantage (namely, comparative STEM advantage), because they are assigned to classrooms with peers who perform at different levels in STEM and non-STEM subjects. This identification allows us to

[23]For example, the student with the highest absolute STEM advantage in a classroom of 20 students would have an ordinal rank of absolute STEM advantage equal to 20 and a comparative STEM advantage equal to 1 ($\frac{20-1}{20-1}$). At the same time, the student with the lowest absolute STEM advantage in a classroom of 20 students, would have an ordinal rank of absolute STEM advantage equal to 1 and a comparative STEM advantage of 0 ($\frac{1-1}{20-1}$).

[24]The relationship between comparative STEM advantage and STEM performance is increasing, but it shows large variation. The top panel of Figure A4 shows this variation in comparative STEM advantage, with respect to average STEM performance. This large variation is even more pronounced in the middle of the STEM performance distribution. The association between non-STEM performance and comparative STEM advantage is rather weak. The variation in comparative STEM advantage remains constant for every decile of non-STEM performance.

control for average classroom characteristics that could confound our estimates of interest.

Variation in comparative STEM advantage stems from differences in the dispersion of absolute STEM advantage among *random* peers in classrooms with the same average characteristics. Classrooms may have different dispersion of absolute STEM advantage because of their small size.[25] The schematic in Figure 5 provides intuition about the source of the identifying variation in comparative STEM advantage. It considers two students with the same absolute STEM advantage X. The students are randomly assigned to different classrooms in school A. Classrooms 1 and 2 are identical except for the dispersion of absolute STEM advantage among students. Therefore, the two students have different values of comparative STEM advantage. Our identification strategy is similar to that of Elsner and Isphording (2017) and Murphy and Weinhardt (2018), who estimate the impact of performance rank on future educational attainment. These papers exploit variation across different school-cohorts, while our approach considers randomly created peer groups (i.e., classrooms) within the same school-cohort.

4.3 Empirical Strategy

We estimate the effect of comparative STEM advantage on subsequent STEM study outcomes using the following regression specification:

$$Y_{ijst} = \alpha + \beta Comparative\ STEM\ Advantage_{ijst} + f(a_{ijst}) + X'_{ijst}\,\gamma + \mu_{jst} + \varepsilon_{ijst} \qquad (4)$$

where Y_{ijst} is the outcome variable for i student, in j classroom, in s school, and t cohort. This can be a dummy indicator that equals to one if a student enrolls in a STEM track in grade 11 or a dummy indicator that equals to one if a student applies to a STEM university degree program 2 years later. We later also use performance in STEM subjects in grades 11 or grade 12, as an outcome variable. Outcome Y depends on comparative STEM advantage, a flexible function of absolute STEM advantage, $f(a_{ijst})$, individual characteristics, X_{ijst}, and classroom FE, μ_{jst}.[26]

Vector X contains student gender, year of birth, and an individual's performance in STEM

[25] Larger classrooms would have a dispersion of student ability closer to the population dispersion due to the central limit theorem, making dispersion across classrooms less likely to differ. Figure A5 shows substantial variation in the standard deviation of absolute STEM advantage within each classroom.

[26] An alternative approach would be to add classroom-specific controls (average STEM and non-STEM performance, average absolute STEM advantage, class size) and school FE, instead of classroom FE. Our results are robust to both specifications.

and non-STEM subjects.[27] Standard errors are clustered at the school-cohort level.[28] We estimate specification (4) using OLS.[29] We model $f(a_{ijst})$ in many ways, but our preferred specification controls for absolute STEM advantage nonlinearly using 10 indicators for a student's decile position in the sample-wide distribution of absolute STEM advantage. In every specification with female interactions, every regressor is interacted with the female dummy.

We are able to interpret the estimates of interest β as the causal effect of comparative STEM advantage on future STEM study choice, distinct from the effect of absolute STEM advantage, under two assumptions. The first assumption requires comparative STEM advantage to be uncorrelated with the error term, conditional on absolute STEM advantage, individual controls, and classroom FE. This assumption would be violated if some students were able to sort themselves into classrooms based on their expected comparative STEM advantage. This self-sorting behavior is not possible in the institutional setting we exploit in this study. In our quasi-experimental environment, high school students who attend the same school are assigned to classrooms in alphabetical order based on their surname. Students with a surname starting with a letter earlier in the alphabet are given a classroom number smaller than the classroom number given to students with a surname starting with a letter later in the alphabet. Table 2 provides evidence that the alphabetical assignment to classrooms is practically random. This table shows that students are indeed randomly assigned to classrooms and classroom numbers are not systematically associated with differences in student characteristics or average or median classroom observable characteristics. In particular, we show that classrooms have similar average GPA (overall and by gender), proportion of females, and average STEM and non-STEM performance (overall and by gender).

The second assumption requires that any specification error in the functional form for absolute STEM advantage, $f(a)$, be uncorrelated with the error term in specification (4). The comparative STEM advantage is the rank measure of absolute STEM advantage. Therefore, any misspecification in the functional form for absolute STEM advantage must be uncorrelated with comparative STEM advantage. If not, β may pick up possible misspecification error in the functional form of absolute STEM advantage, rather than the actual effect of comparative STEM advantage. We

[27] As depicted in Figure 2 and Panel A of Table 1, scores in non-STEM subjects are higher on average than scores in STEM subjects. While this difference in level does not impact our measure of absolute STEM advantage, there could be a direct effect of a student's average score in STEM and non-STEM subjects, which could potentially differ by gender. Indeed, the literature has found that females may be more sensitive to test scores than males (Owen, 2010). Specification (4) disentangles the score level influence by controlling for STEM and non-STEM average raw performance.

[28] We follow Abadie et al. (2017), who suggest clustering at a higher level of aggregation than that of the randomization, subject to finite sample issues.

[29] Ordinary least squares has been found to be as good at modeling classification problems as logistic regression or linear discriminant analysis (Friedman et al., 2001).

provide evidence of the validity of this assumption by showing that our results are robust to using different functional forms for absolute STEM advantage.

5 Results

5.1 Initial STEM Track Enrollment

Table 3 shows our estimates for specification (4), using two different outcomes. For each outcome, we estimate six regressions that vary only in terms of the functional form of absolute STEM advantage used in the specification, while all other variables remain the same. The top panel shows estimates when the outcome is a student's decision to enroll in a STEM track in grade 11. This is the first specialization decision the student ever has to make in her school career. In the first five columns, we use increasing order polynomial functions for absolute STEM advantage. Column (6) is our most preferred specification, and controls for absolute STEM advantage in a flexible way. In particular, we include dummy indicators for each of the 10 different decile levels of absolute STEM advantage. The estimated effect of comparative STEM advantage remains almost unchanged in all functional forms.

The estimated coefficient of comparative STEM advantage is not significant for males, but it is significant and equal to 0.19 for females (=0.030+0.161). This means that females who are ranked at the top of their classroom distribution in grade 10, are roughly 19% more likely to enroll in a STEM track in grade 11 than females who are ranked at the bottom of their classroom distribution, ceteris paribus. Our results suggest that an increase in comparative STEM advantage by 10%, or approximately two positions in the classroom ranking,[30] increases the likelihood of choosing a STEM track in grade 11 by 1.9 percentage points for females. Given that classroom, school, and cohort characteristics, as well as student characteristics and academic performance in levels are held constant, we consider the estimated effect of comparative STEM advantage to be sizable.

This suggests that students with a lower comparative STEM advantage may underinvest in STEM enrollment compared with similar students, who are randomly assigned to different classrooms. Our findings suggest that between 4 and 6 percentage points of the 34-percentage-point gender gap (or 12-18%) in initial STEM specialization in high school are attributable to the influence of the comparative STEM advantage.[31]

[30] The average classroom size in our sample is 20 students. Therefore, an increase in comparative STEM advantage by 2 positions corresponds to an increase of 10% in the percentile rank of STEM advantage.

[31] We multiply the difference in comparative STEM advantage between females who go into STEM track and females who go into non-STEM track with the full effect of comparative STEM advantage on the likelihood of

5.1.1 Longer-term Outcomes

We examine the effect of comparative STEM advantage on the likelihood of applying to a 4- or 5-year university STEM degree, as well as on performance in STEM courses in grades 11 and 12. The second panel of Table 3 shows the estimates for specification (4) using a dummy indicator that takes the value of 1 if a student applies to a STEM degree program, and 0 otherwise, as the outcome variable. This specification only includes students who enrolled in a STEM track in the previous grade. Comparative STEM advantage in grade 10 has a positive impact only for females on future application to a STEM degree program. In particular, an increase in comparative STEM advantage equivalent to a move up by two rank places in the classroom distribution is associated with an increase in the likelihood of applying for a STEM degree program by almost 1% for females. The effects are not statistically different from zero for males. This result indicates that one's comparative STEM advantage has long-lasting implications 2 years later. It is likely that between grade 10 and the end of grade 12, students interact with other peers in addition to their grade 10 classmates. Nevertheless, the effect of grade 10 comparative STEM advantage is long-lasting and significant.

We further examine the effect of comparative STEM advantage on student performance in STEM subjects in grades 11 and 12. A higher comparative STEM advantage may encourage study efforts in STEM subjects. Table 4 displays the results. A higher comparative STEM advantage is associated with a significant increase in STEM performance only for females in grade 11 (top panel) and grade 12 (bottom panel). In particular, a 10% increase in comparative STEM advantage increases females' performance in STEM by 2.5%[32] in grade 11 and 4.3% in grade 12. Both effects remain similar across all columns of Table 4. We do not find any statistically significant effect of comparative STEM advantage on future performance for males.[33]

5.1.2 Nonlinear Effects

Thus far, our main results show the average impact of comparative STEM advantage across different rank positions. In this section, we investigate the potential nonlinear effects of comparative

STEM track choice (in our preferred specification, column 6 of Table 3) to identify how much more likely females who go into a non-STEM track would be to choose a STEM track if not for the effect of rank in STEM advantage: 0.251(0.030+0.161)=0.048 or 4.8 %. An alternative way would be to compute the effect of rank for females and males. We multiply the effect of comparative STEM advantage for females by their average rank (0.19+0.409=0.077) and multiply the effect of comparative STEM advantage for males by their average rank (0.30+0.487=0.0146). We subtract these two numbers (0.062) to provide the different impact of rank for females and males.

[32] The estimate is 0.535 for females. Since test score performance is out of 20, this results in an increase equivalent to about 2.5%.

[33] These results are in line with those of (Goulas and Megalokonomou, 2015).

STEM advantage on students' specialization decisions.

Figure 6 shows the effect of comparative STEM advantage across all possible values of it (0.05 intervals), separately for males and females. In this figure, we focus on a student's decision to enroll in a STEM track at the beginning of grade 11. Most of the effects appear small for males and are mainly concentrated in the middle of the distribution (top figure), while they become insignificant at the top part of the comparative STEM advantage distribution. For females, the effects are negative for low values of comparative STEM advantage, but become positive and significant across the top-half of the distribution of comparative STEM advantage. Overall, it seems that the effects of the comparative STEM advantage increase only for females when moving from lower to higher rank positions.

Figure A6 shows the average effect of comparative STEM advantage for different quintiles of STEM and non-STEM performance distributions. In this figure, we focus again on a student's decision to enroll in a STEM track at the beginning of grade 11. An interesting feature of this analysis is that the effect of comparative STEM advantage shows a different pattern when we focus on the different quintiles of STEM and non-STEM performance.

In particular, consider the marginal effect of comparative STEM advantage by quintile of STEM performance shown in the top figure. For students at the top and bottom of the STEM distribution, the effect of rank is small or insignificant. The effect seems to have a U shape, while the significant effects are positive and mainly concentrated in the middle of the STEM ability distribution. Students in the second-highest quintile of the STEM distribution (quintile 4) are influenced the most by comparative STEM advantage.

The marginal effect of comparative STEM advantage is found to increase when moving from lower to higher quintiles of non-STEM performance (bottom figure). The effect is positive across the distribution, but larger for students in the top quintiles of the non-STEM performance distribution. As shown earlier, higher quintiles of non-STEM performance contain more females than males (Figure A3). This could explain why females are more likely to be affected by comparative STEM advantage.

5.1.3 Comparative STEM Advantage among Classmates of Same Gender

In this section, we investigate whether the effect of comparative STEM advantage is more pronounced among classmates of the same gender. Table 5 shows estimates using specification (4), where comparative STEM advantage is computed only among same-gender classmates. For females, the effect of comparative STEM advantage measured with respect only to other female classmates is similar to the main estimates, in which the comparative STEM advantage is computed based on all classmates. The estimates are similar for both outcomes: choice of STEM track in grade 11 (=0.156 vs. 0.161) and application to a STEM university degree program (=0.087 vs. 0.102). This indicates that for females, these two reference groups are similarly used when making social comparisons. Among males, the effect of comparative STEM advantage with respect only to their male classmates is negative and small in magnitude; in the main results, in contrast (Table 3), they were positive and insignificant.

5.1.4 Comparative STEM Advantage with Respect to School-Cohort

In this section, we investigate the impact of comparative STEM advantage computed within a student's school-cohort instead of the classroom. The outcome variables we focus on are a student's STEM track choice in grade 11 and application to a STEM university degree program. We use specification (4) for the estimates, and comparative STEM advantage is computed based on a student's school-cohort peers. In the previous section, we exploited variation in the dispersion of absolute STEM advantage across classrooms, controlling for classroom fixed effects (FE); in this section, we exploit variation that arises from dispersion of the absolute STEM advantage across different cohorts in the same school.

Table 6 shows the estimates, which indicate that comparative STEM advantage has a much smaller and weaker effect when it is computed within the school-cohort instead of the classroom. The estimates are now much smaller compared with the main results (0.037 vs. 0.161 and 0.063 vs. 0.102) and statistically insignificant. In contrast, estimates in the main results were statistically significant and differed for males and females. Overall, the influence of comparative STEM advantage among same school-cohort peers is weaker than that of same-classroom peers on later STEM study choices.

This finding is intuitive for at least two reasons. First, students may be more likely to interact with peers they share more instruction time with. Students may not be as aware of the performance of their school-cohort peers as they are of their classmates' performance. Second, a school cohort is, by definition, a larger set of students than a classroom. School cohorts may be more representative of the general student population attending a school over time than classrooms are. Thus, there may be less variation in student characteristics between different 10^{th} grade cohorts within the same school than between classrooms within the same school-cohort.

5.1.5 Robustness Checks

Thus far we have assumed that comparative STEM advantage is orthogonal to the error term conditional on absolute STEM advantage, student and classroom characteristics. In this section, we conduct a battery of robustness checks and discuss potential sources of bias. We start by providing evidence of the robustness of our results with respect to sample attrition. We then show that our results are robust to using different measures of school performance to calculate absolute and comparative STEM advantage. In addition, we show that our results are robust to different definitions of STEM subjects and degree programs. Finally, we report the effect of comparative non-STEM advantage.

5.1.6 Sample Attrition

Attrition in our sample could happen for two reasons. First, some students may drop out or transfer from the school during their 10$^{\text{th}}$ grade.[34] We define these students as *"early leavers."* Second, some students may drop out or transfer from the school at the end of 10$^{\text{th}}$ grade, after having completed the grade.[35] We define these students as *"attriters."* We do not have neither early leavers' performance at the end of grade 10 nor their future enrollment choices. In contrast, we have attriters' performance at the end of grade 10 but not their future enrollment choices. Males are more likely to leave grade 10 early or drop out at the end of grade 10 than females (Table A4). In our sample, 8.2% of males and 4.3% of females are early leavers, and 17.2% of males and 13.3% of females are attriters.[36] One might worry that students with a lower comparative STEM advantage would be more likely to drop out during or after the end of grade 10, which could introduce bias in our estimates. Table A5 shows no strong association between classroom performance (measured by classroom average GPA) and gender difference in early leavers and attriters.

Then, we explore the association between comparative STEM advantage and student attrition at the end of grade 10.[37] We estimate specification (4) using an indicator variable that takes the value of 1 if a student is an attriter, and 0 otherwise, as an outcome. Table 7 shows that sample attrition is not associated with comparative STEM advantage. To further alleviate any concerns

[34]The compulsory schooling age in Greece is 15 years, the age at which most students graduate from 9$^{\text{th}}$ grade. This suggests that, potentially, students who are likely to drop out of school may do so before they start 10$^{\text{th}}$ grade. Survey data collected by Eurostat revealed an overall school dropout rate of 14.2% for Greece in 2009, identical to the EU average at the time(Directorate-General for Education, Youth, Sport and Culture, 2019).

[35]We are not able to follow students who move to another school.

[36] These rates are not too far off the mobility rates recorded in other parts of the world. For example, in 2017-18 in Colorado, the school-level average mobility rate was 15.9% for males and 15.9% for females (`https://www.cde.state.co.us/cdereval/mobility-stabilitycurrent`)

[37]We cannot replicate this analysis for early leavers, since these students drop out before taking the exams. Thus, the comparative STEM advantage cannot be computed for these students.

about survival bias, we show that our results remain robust when we employ inverse probability weights (IPWs) to control for sample attrition. Table A6 shows the results for specification (4), without and with attrition weights. Our results remain qualitatively unaffected when sample attrition is accounted for (0.202 vs. 0.182 and 0.161 vs. 0.139 for the quadratic and nonlinear specifications, respectively).

5.1.7 Impact of Comparative STEM Advantage Using First-semester Performance

In our main analysis we use final exam performance to compute student comparative STEM advantage. We employ final exam performance for two reasons. First, final exam performance provides a more comparable measure of student performance. Every student in a specific grade and school takes the same final test in every compulsory course, regardless of their classroom assignment. This allows us to obtain a comparable measure of performance across different classrooms within a specific school-cohort. The final exam is designed collectively by all of the instructors teaching each course, within each school. Thus, the final exam is less likely to be influenced by a particular teacher's grading standards or inflation. Second, students decide which track they want to enroll in after they receive their final exam scores. Therefore, final exam scores reflect the most recent information students receive right before making their STEM specialization decision.

One might worry that each student's final exam performance could be affected by interactions with their classmates during the school year. Thus, a student's peers may simultaneously influence her absolute and comparative STEM advantage, measured at the end of the school year. This leads to potential estimation bias. To alleviate this concern, we reproduce our results from specification (4) using student performance in the first semester of grade 10, which is the earliest instance of performance measurement in high school. Table 8 shows these estimates, which remain almost unchanged compared with the main estimates. In particular, a 10% increase in comparative STEM advantage increases females' likelihood of enrolling in a STEM track in 11^{th} grade by 1.7 percentage points, while the equivalent estimate for the main effect was 1.6 percentage points. The results are robust to the use of the first-semester performance instead of final exam performance for both outcome variables. The impact on the STEM degree application follows the same pattern when we use first-semester performance (=0.45) compared with the main results (=0.102), but the magnitude is smaller. For males, comparative STEM advantage seems to not have a significant impact on their study decisions.

5.1.8 Different Definitions of STEM Subjects and Degree Programs

While a vast literature has focused on the underenrollment of women in STEM disciplines, recent studies argue that gender differences in enrollment are particularly concentrated in math-intensive science fields (Kahn and Ginther, 2017). Our definition of STEM degree programs thus far includes only Sciences, Engineering, and Technology departments and not Economics, Business, and Health Science.[38] In Table A7 we show our main results when Economics and Business departments are included in the definition of STEM (second panel) and when Health Science is included (third panel).[39] In both cases, the results are similar to the main ones (shown in the first panel for reference).

In our main analysis, we define STEM subjects in grade 10 using a broad definition, in which we include all subjects related to Algebra, Chemistry, and Physics. We show that our results are robust to narrower definitions of STEM subjects. Table A8 displays the results using each of the following subjects separately in the definition of STEM subjects: Algebra, Chemistry[40] and Physics[41]. The first column shows the baseline results when all three subjects are considered to be STEM subjects as a benchmark, while the last three columns show results when comparative STEM advantage is computed separately using only one of the three STEM subjects. The main estimates are now 0.152 (Algebra), 0.151 (Chemistry), and 0.110 (Physics) compared with 0.161, which is the main estimate for the interaction term when we average across a student's performance in these three subjects. Again, the results remain robust when we use different definitions of STEM subjects in grade 10.

5.1.9 The Effect of Comparative Non-STEM Advantage

In this section we analyze whether comparative non-STEM advantage has an effect on future study choices. We rank students within each classroom based on their absolute non-STEM advantage and compute their comparative non-STEM advantage using (3). Table A9 reports the results for specification (4), when comparative non-STEM advantage is used. As expected, comparative non-STEM advantage has a negative and significant effect on track choice at the end of grade 10. The effect is significant for females, but not significantly different from zero for males. The magnitudes

[38] We follow the International Standard Classification of Education (ISCED) and define STEM as Natural Sciences, Mathematics and Statistics (ISCED-05); Information and Communication Technologies (ISCED-06); and Engineering, Manufacturing and Construction (ISCED-07).

[39] Students from both STEM and non-STEM tracks can apply to Economics/Business and Health Science departments.

[40] These are the subjects in which females perform significantly better than males.

[41] This is the only subject in which there is no significant difference between male and female performance.

of the estimates are similar to those reported in Table 3. Nevertheless, comparative non-STEM advantage has no effect on university applications.

6 Potential Mechanisms

In the previous sections, we presented evidence that comparative STEM advantage influences males and females differently in their STEM specialization decisions. In this section we discuss the potential mechanisms behind the different responsiveness to comparative STEM advantage for males and females, using the terminology used in the model in Section 2.

Our theoretical framework considers two potential factors of the heterogeneous influence of comparative STEM advantage on STEM specialization for males and females. The first is the marginal monetary return to relative competence and the second is the nonmonetary return of choosing a specific specialization. If one occupation has a lower (higher) marginal return to relative competence, λ, than the other occupation, it would require a higher (lower) comparative advantage to justify specializing in the discipline related to the first occupation. Similarly, if one occupation is associated with higher (lower) nonmonetary marginal utility, p, than the other occupation, it would require a lower (higher) advantage compared with one's peer(s) to justify specializing in the discipline related to the first occupation.

Males and females may have different monetary returns to STEM occupations, λ^S. The gender difference in monetary return of STEM occupations has been established in the empirical literature (O'Neill, 2003; Weichselbaumer and Winter-Ebmer, 2005; Rose, 2010; Perfect, 2011). In recent work, Kahn and Ginther (2018) find that gender pay gap in STEM occupations in the United States is 5.3 and 28.2 percent for unmarried and married individuals, respectively. Survey results in Greece show that males indeed enjoy a higher salary than females (European Institute for Gender Equity, 2017), which may reflect a potential gender pay gap in STEM-related occupations. This may suggest that males have a higher monetary marginal return to relative competence in STEM versus non-STEM.

If males have higher monetary return of STEM occupations than females ($\lambda_m^S > \lambda_f^S$), the decision rule (1) differs by gender:

$$\frac{\frac{\alpha_i^S}{\alpha_i^{NS}}}{\frac{\alpha_{-i}^S}{\alpha_{-i}^{NS}}} > \frac{p_{i,m}^{NS} \cdot \lambda_m^{NS}}{p_{i,m}^S \cdot \lambda_m^S} \qquad \qquad \frac{\frac{\alpha_i^S}{\alpha_i^{NS}}}{\frac{\alpha_{-i}^S}{\alpha_{-i}^{NS}}} > \frac{p_{i,f}^{NS} \cdot \lambda_f^{NS}}{p_{i,f}^S \cdot \lambda_f^S} \tag{5}$$

where in both equations the LHS represents the comparative STEM advantage. Assume, for simplicity, that $p_m^{NS} = p_m^S = p_f^{NS} = p_m^S = 1$ and that $\lambda_m^{NS} = \lambda_f^{NS}$. Assume also that males and females compete with peers of the same competence. Therefore, the two decisions rules (5) become

$$\frac{\frac{\alpha_i^S}{\alpha_i^{NS}}}{\frac{\alpha_{-i}^S}{\alpha_{-i}^{NS}}} \cdot \frac{\lambda_m^S}{\lambda_m^{NS}} > 1 \qquad \frac{\frac{\alpha_i^S}{\alpha_i^{NS}}}{\frac{\alpha_{-i}^S}{\alpha_{-i}^{NS}}} \cdot \frac{\lambda_f^S}{\lambda_f^{NS}} > 1 \tag{6}$$

Since $\lambda_m^S > \lambda_f^S$, and $\lambda_m^{NS} = \lambda_f^{NS}$, females require a higher comparative STEM advantage than males to choose a STEM specialization.

The second mechanism behind our theoretical investigation that could explain the differential effect of comparative STEM advantage on males and females is the nonmonetary return of choosing a specific specialization. Nonmonetary returns refers to preferences or tastes. Males and females may face different nonmonetary returns to specializing in STEM. First, STEM-related occupations tend to be more competitive than non-STEM-related occupations. Several papers find that females tend to shy away from competition (Niederle and Vesterlund, 2007; Gneezy et al., 2003; Ors et al., 2013; Orrenius and Zavodny, 2015; Landaud et al., 2016). Second, many studies have examined the societal and environmental influences that shape female attitudes toward STEM subjects and occupations.[42] The literature has also explored the role of teacher biases,[43] parental investments, and beliefs,[44] in shaping females preferences in relation to STEM-related fields. Lastly, women are underrepresented in STEM occupations in Greece (European Institute for Gender Equity, 2019). Dille (2018) and Yu (2020) claim that greater exposure to positive female role models and mentors, especially in the technological sector, increases females' preference for STEM-related occupations.

If females face lower nonmonetary returns in STEM than males ($p_f^S < p_m^S$), they would face different decision rules. Following a similar rationale as in the previous part of the mechanism, females need to have a higher comparative STEM advantage than males to choose a STEM specialization.

7 Conclusion

In this paper, we present evidence that students may use two dimensions of comparison when they make decisions about school track, university degree, and occupation. The first dimension is

[42] Cvencek et al. (2011) find that as early as elementary school, boys already associate themselves with math and girls with reading; Guiso et al. (2008) argue that the gender gap is smaller in more gender-equal countries. Nollenberger et al. (2016), by studying second-generation immigrants, find that about two-thirds of the gender math gap can be attributed to parents' cultural attitudes.

[43] Lavy and Sand (2015) and Lavy and Megalokonomou (2019) document that teacher gender biases may affect females' likelihood of specializing in STEM degrees and STEM-related occupations.

[44] Eccles and Jacobs (1986) and Eccles et al. (1990) have investigated how the mother's beliefs about her daughter's ability impacts performance and the decision to take additional math courses.

what we call *absolute advantage*, which refers to the within-individual relative academic strengths and weakness in STEM subjects compared with non-STEM subjects. The second dimension is the *comparative advantage* and concerns a student's relative standing in terms of her absolute advantage within her peer group. While the effect of absolute advantage has been widely explored, we are the first to disentangle the causal effect of comparative STEM advantage from the effect of absolute STEM advantage on future specialization decisions.

We use data from a large number of high schools in Greece that span from 2001 to 2009 and are linked to students' university degree applications. We exploit the institutional setting in Greece by which students are practically randomly assigned to classrooms at the beginning of grade 10. We proxy a student's comparative advantage in STEM subjects by using a their rank in absolute STEM advantage in grade 10. This rank is quasi-randomly assigned to students, given their absolute STEM advantage. We present extensive evidence to support the validity of our identification strategy by showing that students' classroom allocation in grade 10 is practically random. We then examine the effect of a student's comparative STEM advantage on her subsequent decision to enroll in a STEM track in grade 11, on subsequent STEM performance, and on the decision to apply for a 4- or 5- year university degree in a STEM major 2 years later.

We find that females perform at least as well as males in STEM subjects, but much better than males in non-STEM subjects. This implies that females have a lower absolute STEM advantage with respect to their classmates and a lower comparative advantage. We find that increasing a student's comparative advantage in STEM within her classroom by two positions increases her likelihood of enrolling in a STEM track by 1.9% for females, but has much smaller or insignificant effect on males. We also find that a student's comparative advantage in STEM in grade 10 has longer-term implications. In particular, we find that an increase in a student's 10^{th} grade comparative STEM advantage by 10% increases her likelihood of applying to a STEM university degree program by around 1% for females; males are less or not affected. Comparative STEM advantage has a significant effect on STEM performance in grades 11 and 12. Additionally, we find similar effects when the comparative advantage is computed with respect to the same-gender peers in the classroom or to the school-cohort.

We conduct several robustness exercises to provide further credibility for causal interpretation of the effects of comparative STEM advantage. First, we show that a student's comparative advantage in STEM subjects is uncorrelated with school dropout decisions. Second, we show that our results are robust to using students' performance measured earlier in grade 10. Third, we show that our results remain similar when we use alternative definitions of STEM subjects and university degree programs.

We develop a simple theoretical model to explain the role of comparative STEM advantage in STEM study decisions. From this model, we derive two mechanisms to explain the larger effect of comparative advantage on females. Lower monetary returns in STEM occupations for females and different preferences for STEM occupations may explain the higher impact of comparative STEM advantage on STEM study choices.

Our analysis is highly policy-relevant as it provides an additional channel to explain the under-representation of women in STEM tracks. Our findings suggest that 4-6 percentage points of the 34-percentage-point gender gap (or 12-18%) in STEM specialization in high school are attributable to the influence of the comparative STEM advantage. Our research concludes that competition discourages females from studying STEM early on, in the first instance of specialization. This suggests that if females were given the option to specialize away from STEM study at an even earlier stage than grade 11, it is likely they would do so and would acquire even less STEM-related training during their school career.

The method we use to measure comparative advantage and to identify the strengths within the individual and across individuals is general and could be applied to other contexts. Any context in which comparisons with competitors emerge along multiple dimensions—such as the labor or the marriage market—could profit from our approach to quantifying the object of comparison. A benefit of using comparative advantage as a measure of relative strength is that it carries economic intuition, and decisions based on comparative advantage are economically justifiable.

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Table 1: **Descriptive Statistics**

	Male	Female	Difference	*p-value*
	(1)	(2)	(3)	(4)
Panel A: Performance in Grade 10				
Algebra	9.433	9.873	0.440	0.000
Physics	10.325	10.373	0.048	0.188
Chemistry	10.405	10.963	0.559	0.000
Modern Greek	12.876	14.220	1.344	0.000
Greek Literature	12.099	13.922	1.824	0.000
Ancient Greek	11.249	12.861	1.612	0.000
Panel B: Constructed Variables in Grade 10				
Own Grade in STEM	10.054	10.403	0.349	0.000
Own Grade in non-STEM	12.074	13.668	1.594	0.000
Class Average Grade in STEM	10.202	10.184	-0.018	0.135
Class Average Grade in non-STEM	12.892	12.881	-0.011	0.329
Comparative STEM Advantage	0.487	0.409	-0.077	0.000
Panel C: Outcome Variables on Track and University Choices				
STEM Track in Grade 11	0.812	0.472	-0.340	0.000
Applied for a STEM Degree	0.627	0.565	-0.062	0.000
Applied for an Economics and Business Degree	0.272	0.228	-0.044	0.000
Applied for a Health Sciences Degree	0.119	0.321	0.203	0.000
Applied for a Humanities Degree	0.363	0.626	0.262	0.000

Notes: Panel A reports gender differences in performance for the six subjects we use to construct our measure for the average performance in STEM and Non-STEM in grade 10. Raw scores are out of 20. Panel B shows the gender differences in one's own and classroom average performance in STEM and Non-STEM subjects, as well as the comparative STEM advantage. Panel C reports the gender differences in track choice and university-related outcomes. Applied for a STEM department is conditional on attending a STEM track in grade 12. Applied for a Humanities department is conditional on attending a non-STEM track in grade 12. For each panel, we report summary statistics for male and female students (columns 1 and 2, respectively); the gender difference between column (2) and (1) (column 3); and p-values for the t-test on the gender difference (column 4).

Table 2: **Evidence of Random Assignment of Students into Classrooms**

	Class Av. GPA	Class Median GPA	Prop. Female	Av. GPA Female	Av. GPA Male	Av. STEM GPA Female	Av. STEM GPA Male	Av. non-STEM GPA Female	Av. non-STEM GPA Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Class number=1	-0.167	-0.249	-0.024	-0.174	-0.104	-0.011	-0.021	-0.183	-0.100
	(0.129)	(0.153)	(0.022)	(0.153)	(0.236)	(0.257)	(0.412)	(0.216)	(0.280)
Class number=2	-0.230*	-0.291*	-0.029	-0.292*	-0.139	-0.191	-0.095	-0.388*	-0.157
	(0.130)	(0.153)	(0.022)	(0.157)	(0.237)	(0.255)	(0.417)	(0.220)	(0.282)
Class number=3	-0.153	-0.206	-0.019	-0.214	-0.043	-0.136	0.018	-0.292	-0.028
	(0.129)	(0.153)	(0.021)	(0.151)	(0.234)	(0.248)	(0.415)	(0.210)	(0.275)
Class number=4	-0.122	-0.175	0.005	-0.168	-0.086	-0.156	-0.067	-0.222	-0.146
	(0.128)	(0.154)	(0.022)	(0.155)	(0.225)	(0.250)	(0.412)	(0.220)	(0.265)
Class number=5	-0.028	-0.083	-0.006	-0.154	0.122	-0.022	0.289	-0.310	0.065
	(0.130)	(0.163)	(0.024)	(0.134)	(0.260)	(0.248)	(0.439)	(0.201)	(0.288)
Obs.	3,432	3,432	3,432	3,426	3,382	3,426	3,382	3,426	3,382
Mean of Y	14.42	14.32	0.55	14.77	13.97	10.72	10.56	13.99	12.54
Av. N. of classes per school	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40
School x Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
F-Stat. Model	2.17	1.76	2.15	1.95	2.00	1.33	1.56	3.16	1.39
P-value of F-model	0.06	0.12	0.06	0.09	0.08	0.25	0.17	0.01	0.23

Notes: The table shows results of the estimated effects of the classroom number on a variety of outcomes. Outcome variables are reported in the column. Specifically, we regress the classroom number on average classroom GPA (column 1), median classroom GPA (column 2), the proportion of females in the classroom (column 3), the average GPA of females in the classroom (column 4), the average GPA of females in the classroom (column 5), the average GPA of females in STEM (column 6), the average GPA of males in STEM (column 7), the average GPA of females in non-STEM (column 8), and the average GPA of males in non-STEM (column 9). Classroom is the unit of observation. F-statistics for the joint significance of the regressors suggest that the classroom number is not associated with differences in classroom-level outcomes. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: **The Effect of Comparative STEM Advantage on Subsequent Tracks and University Choices using Different Functional Forms**

	Linear (1)	Quadratic (2)	Cubic (3)	Quartic (4)	Quintic (5)	Nonlinear (6)
	STEM Track in Grade 11					
Comparative STEM Advantage	0.122***	0.038*	0.062***	0.039*	0.034	0.030
	(0.018)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)
Comparative STEM Advantage × Female	0.153***	0.202***	0.165***	0.159***	0.162***	0.161***
	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Obs.	72,940	72,940	72,940	72,940	72,940	72,940
Mean of Y	0.63	0.63	0.63	0.63	0.63	0.63
St. Dev. Y	0.48	0.48	0.48	0.48	0.48	0.48
Raw Gender Gap Y	-0.34	-0.34	-0.34	-0.34	-0.34	-0.34
	Application for STEM University Degree					
Comparative STEM Advantage	0.070***	-0.040	-0.046*	-0.040	-0.033	-0.014
	(0.024)	(0.026)	(0.026)	(0.027)	(0.027)	(0.028)
Comparative STEM Advantage × Female	0.093***	0.111***	0.112***	0.110***	0.108***	0.102***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Obs.	45,259	45,259	45,259	45,259	45,259	45,259
Mean of Y	0.72	0.72	0.72	0.72	0.72	0.72
St. Dev. Y	0.45	0.45	0.45	0.45	0.45	0.45
Raw Gender Gap Y	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
Classroom FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the estimated effects of comparative STEM advantage on track and university degree choices. The outcome variables are: (a) an indicator for whether a student enrolls in a STEM track in grade 11 (top panel), and (b) an indicator for whether a student applies for a STEM university degree 2 years later (middle panel). For each of the two outcomes, we run different specifications for different degrees of polynomials for the absolute STEM advantage (columns 1-5) and a nonlinear specification, using binary indicators for each decile of the rank (column 6). Each regression controls for student gender, absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and classroom FE. Standard errors are clustered at the school-cohort level. The last row in each panel shows the slope coefficient of the regression of each outcome variable on a female indicator, reflecting the gender gap in that outcome. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4: **The Effect of Comparative STEM Advantage on Future Performance**

	Linear (1)	Quadratic (2)	Cubic (3)	Quartic (4)	Quintic (5)	Nonlinear (6)
	STEM Performance in Grade 11					
Comparative STEM Advantage	-0.190	0.292**	0.298**	0.204	0.190	0.067
	(0.135)	(0.141)	(0.143)	(0.151)	(0.151)	(0.153)
Comparative STEM Advantage × Female	0.570***	0.570***	0.439***	0.441***	0.455***	0.462***
	(0.145)	(0.145)	(0.149)	(0.152)	(0.152)	(0.151)
Obs.	68,425	68,425	68,425	68,425	68,425	68,425
Mean of Y	10.22	10.22	10.22	10.22	10.22	10.22
St. Dev. Y	5.20	5.20	5.20	5.20	5.20	5.20
	STEM Performance in Grade 12					
Comparative STEM Advantage	-0.043	0.213	0.262	0.156	0.143	0.062
	(0.198)	(0.210)	(0.215)	(0.226)	(0.226)	(0.226)
Comparative STEM Advantage × Female	0.839***	0.899***	0.798***	0.783***	0.794***	0.786***
	(0.205)	(0.205)	(0.211)	(0.215)	(0.215)	(0.214)
Obs.	68,425	68,425	68,425	68,425	68,425	68,425
Mean of Y	11.06	11.06	11.06	11.06	11.06	11.06
St. Dev. Y	5.45	5.45	5.45	5.45	5.45	5.45
Classroom FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports results of the estimated effects of comparative advantage using the main specification (4), while two outcomes are used: (1) a student average performance in STEM subjects at the end of 11^{th} grade (top panel) and (2) a student's average performance in STEM subjects at the end of 12^{th} grade (bottom panel). For each of the two outcomes we run different specifications for different degrees of polynomials for STEM advantage (columns 1-5) as well as a nonlinear specification, using dummy variables for each decile of rank (column 6). Each regression controls for student gender, absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and classroom FE. Standard errors are clustered at the school-cohort level. The last row in each panel shows the slope coefficient of the regression of each outcome variable on a female indicator, reflecting the gender gap in that outcome. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5: **The Effect of Comparative STEM Advantage among Same Gender Classmates on Subsequent Tracks and University Choices**

	Linear (1)	Quadratic (2)	Cubic (3)	Quartic (4)	Quintic (5)	Nonlinear (6)
	STEM Track in Grade 11					
Comparative STEM Advantage Same Gender Classmates	-0.005	-0.042***	-0.025*	-0.035***	-0.035***	-0.038***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Comparative STEM Advantage Same Gender Classmates × Female	0.165***	0.194***	0.164***	0.157***	0.158***	0.156***
	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Obs.	72,911	72,911	72,911	72,911	72,911	72,911
Mean of Y	0.63	0.63	0.63	0.63	0.63	0.63
St. Dev. Y	0.48	0.48	0.48	0.48	0.48	0.48
Raw Gender Gap Y	-0.34	-0.34	-0.34	-0.34	-0.34	-0.34
	Application for STEM University Degree					
Comparative STEM Advantage Same Gender Classmates	0.026	-0.014	-0.017	-0.014	-0.013	-0.006
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Comparative STEM Advantage Same Gender Classmates × Female	0.089***	0.092***	0.093***	0.092***	0.092***	0.087***
	(0.023)	(0.023)	(0.023)	(0.024)	(0.024)	(0.024)
Obs.	45,242	45,242	45,242	45,242	45,242	45,242
Mean of Y	0.72	0.72	0.72	0.72	0.72	0.72
St. Dev. Y	0.45	0.45	0.45	0.45	0.45	0.45
Raw Gender Gap Y	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
Classroom FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports results of the estimated effects of comparative advantage using the main specification (4), while the comparative advantage is computed using the within-classroom rank across classmates of the same gender. We exclude classrooms with only one female or only one male student. For each of the two outcomes (STEM track choice in grade 11 and application to a STEM degree program), we run different specifications for different degrees of polynomials for STEM advantage (columns 1-5) as well as a nonlinear specification that uses dummy variables for each decile of rank (column 6). Each regression controls for student gender, absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and classroom FE. Standard errors are clustered at the school-cohort level. The last row in each panel shows the slope coefficient of the regression of each outcome variable on a female indicator, reflecting the gender gap in that outcome. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6: **The Effect of Comparative STEM Advantage within School-Cohort on Subsequent Tracks and University Choices**

	Linear (1)	Quadratic (2)	Cubic (3)	Quartic (4)	Quintic (5)	Nonlinear (6)
	STEM Track in Grade 11					
Cohort Comparative STEM Advantage	0.231***	0.107***	0.163***	0.147***	0.138***	0.135***
	(0.021)	(0.027)	(0.027)	(0.031)	(0.031)	(0.031)
Cohort Comparative STEM Advantage × Female	0.056*	0.159***	0.083**	0.049	0.054	0.037
	(0.032)	(0.034)	(0.036)	(0.037)	(0.037)	(0.038)
Obs.	72,943	72,943	72,943	72,943	72,943	72,943
Mean of Y	0.63	0.63	0.63	0.63	0.63	0.63
St. Dev. Y	0.48	0.48	0.48	0.48	0.48	0.48
Raw Gender Gap Y	-0.34	-0.34	-0.34	-0.34	-0.34	-0.34
	Application for STEM University Degree					
Cohort Comparative STEM Advantage	0.131***	-0.031	-0.041	-0.033	-0.020	0.016
	(0.030)	(0.036)	(0.036)	(0.041)	(0.041)	(0.043)
Cohort Comparative STEM Advantage × Female	0.056	0.099**	0.098**	0.096*	0.088*	0.063
	(0.043)	(0.045)	(0.046)	(0.049)	(0.049)	(0.049)
Obs.	45,269	45,269	45,269	45,269	45,269	45,269
Mean of Y	0.72	0.72	0.72	0.72	0.72	0.72
St. Dev. Y	0.45	0.45	0.45	0.45	0.45	0.45
Raw Gender Gap Y	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
School x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports results of the estimated effects of comparative advantage using the main specification (4), while the comparative advantage is computed using the within school-cohort rank. For each of the two outcomes (grade 11 STEM track choice and application to STEM degree), we run different specifications for different degrees of polynomials for STEM advantage (columns (1)-(5)) as well as a nonlinear specification, using dummy variables for each decile of rank (column 6). Each regression controls for student gender, absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and school-cohort FE. Standard errors are clustered at the school-cohort level. The last row in each panel shows the slope coefficient of the regression of each outcome variable on a female indicator, reflecting the gender gap in that outcome. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: **The Effect of Comparative STEM Advantage on Attrition**

	Attrition at End of Grade 10
Comparative STEM Advantage	0.011
	(0.019)
Comparative STEM Advantage × Female	0.001
	(0.023)
Obs.	86,417
Classroom FE	Yes
Controls	Yes

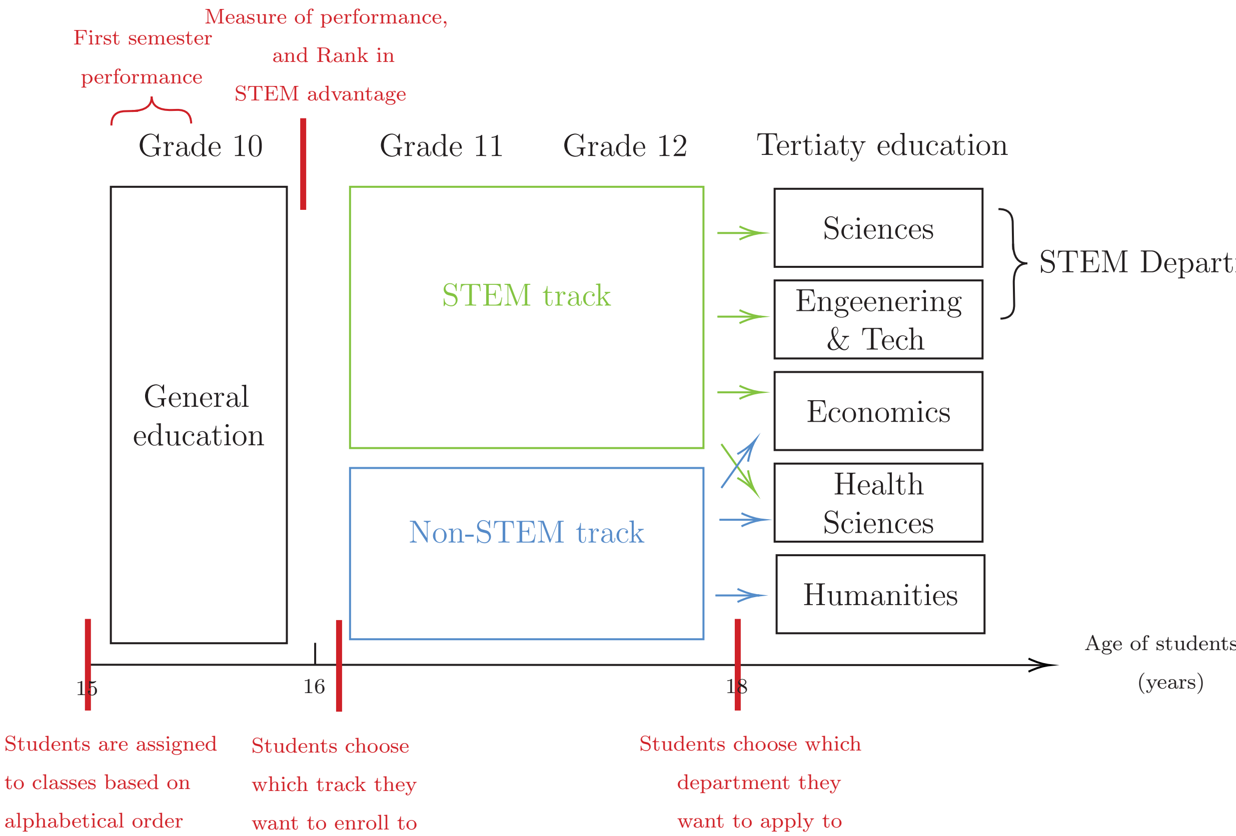
Notes: This table reports results of the estimated effects of the comparative STEM advantage on grade attrition in grade 11. Estimates are derived using specification (4), while the outcome variable is an indicator that becomes equal to one if a student drops out from the sample. Each regression controls for student gender, a second-order polynomial for absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and classroom FE. Standard errors are clustered at the school-cohort level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: **The Effect of Comparative STEM Advantage using First-Semester Performance on Subsequent Tracks and University Choices**

	Linear (1)	Quadratic (2)	Cubic (3)	Quartic (4)	Quintic (5)	Nonlinear (6)
	STEM Track in Grade 11					
Comparative STEM Advantage	0.088***	0.017	0.014	-0.011	-0.008	0.001
	(0.015)	(0.016)	(0.017)	(0.018)	(0.018)	(0.019)
Comparative STEM Advantage × Female	0.188***	0.209***	0.168***	0.174***	0.171***	0.166***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.020)
Obs.	72,887	72,887	72,887	72,887	72,887	72,887
Mean of Y	0.63	0.63	0.63	0.63	0.63	0.63
St. Dev. Y	0.48	0.48	0.48	0.48	0.48	0.48
Raw Gender Gap Y	-0.34	-0.34	-0.34	-0.34	-0.34	-0.34
	Application for STEM University Degree					
Comparative STEM Advantage	-0.016	0.010	-0.008	0.001	0.001	0.007
	(0.020)	(0.023)	(0.023)	(0.025)	(0.025)	(0.026)
Comparative STEM Advantage × Female	0.064***	0.056**	0.051**	0.046*	0.046*	0.044*
	(0.024)	(0.025)	(0.025)	(0.026)	(0.026)	(0.025)
Obs.	45,253	45,253	45,253	45,253	45,253	45,253
Mean of Y	0.72	0.72	0.72	0.72	0.72	0.72
St. Dev. Y	0.45	0.45	0.45	0.45	0.45	0.45
Raw Gender Gap Y	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
Classroom FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

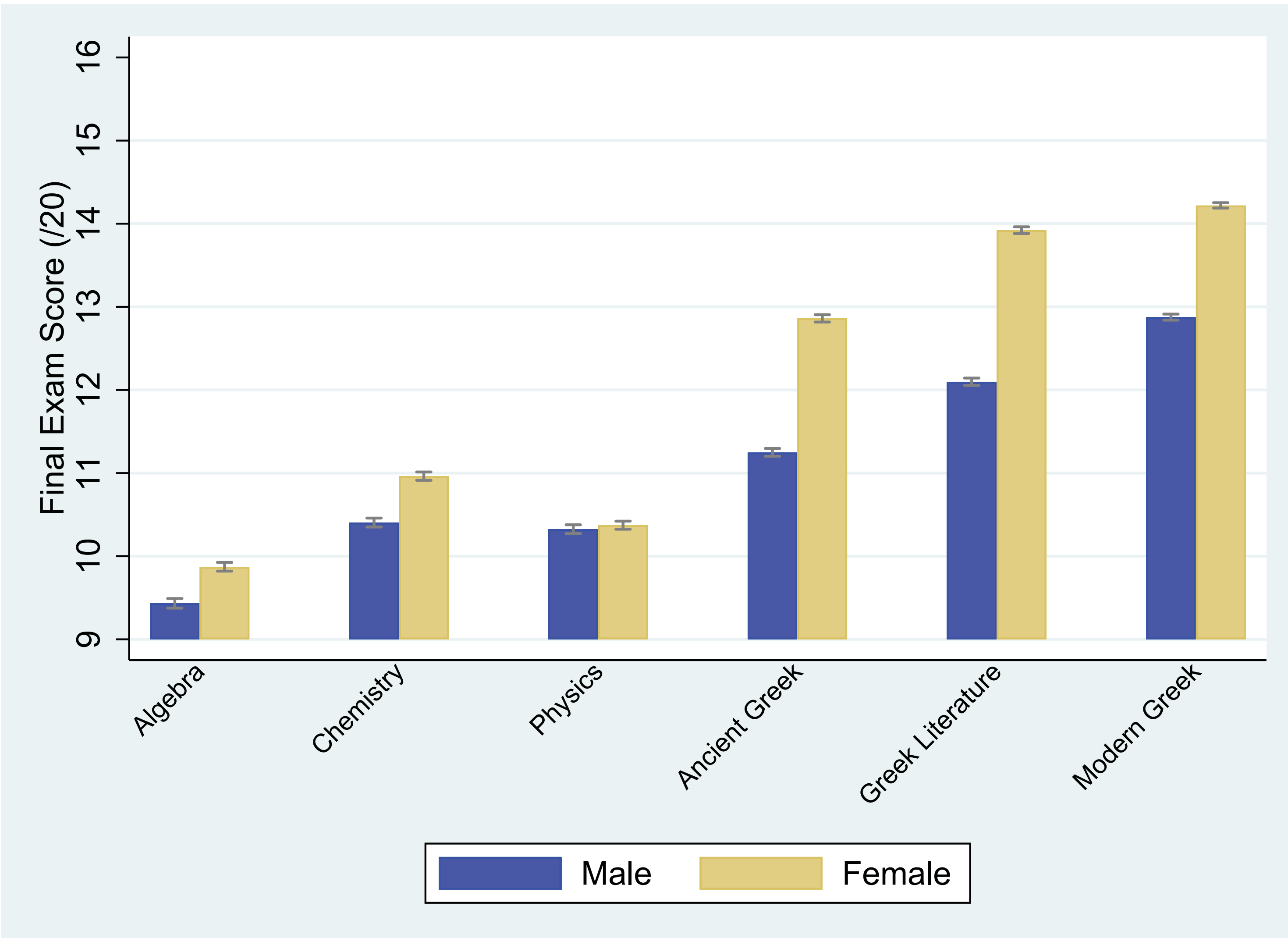
Notes: This table reports results of the estimated effects of comparative advantage using the main specification (4). We now compute comparative advantage based on a student's midterm performance in the first semester, rather than her final exam score (Table 3). Each regression controls for student gender, absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and classroom FE. Standard errors are clustered at the school-cohort level. The last row in each panel shows the slope coefficient of the regression of each outcome variable on a female indicator, reflecting the gender gap in that outcome. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure 1: **Timeline of Students Decision Making in High School and Tertiary Education**



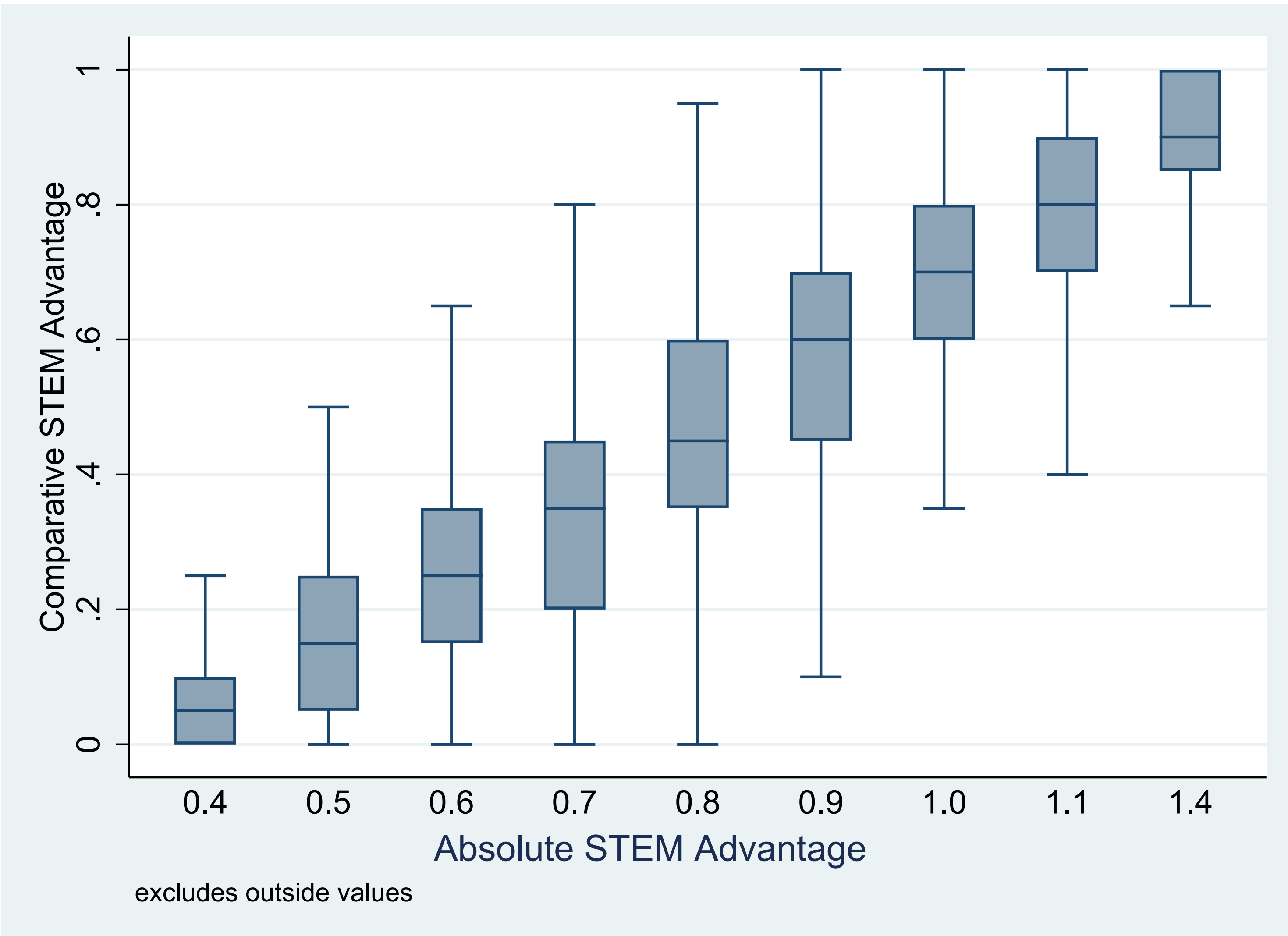
Notes: This figure displays the timeline of student decisions from senior high school to university. At the beginning of grade 10, students are assigned to the high school serving the zone of their residential address. Students start high school at the age of 15. The compulsory school age in Greece is 15, so students who wish to complete only compulsory education drop out before entering the 10^{th} grade. In 10^{th} grade, the first grade of senior high school, students are allocated to classrooms in an alphabetical order based on students' surnames. Students remain in their assigned classroom throughout high school. Students also remain with the same classroom peers for at least every compulsory subject. In 10^{th} grade, all students take 12 compulsory general education courses and 1-2 elective courses. At the end of the school year, students take an exam on all 12 compulsory courses. We use the end-of-year (but also first semester) performance in compulsory subjects to compute their STEM advantage and comparative STEM advantage. Starting from 11^{th} grade, students are able to choose electives that allow them to specialize in one of three tracks: classics, which we identify as non-STEM track, science, and information technology which we identify as STEM tracks. All schools offer these three tracks. Each track offers different subjects, which are compulsory, and all students in a given track have to take those subjects. To apply to a university degree program a student must take standardized national exams in a set of subjects that includes the subjects of their 12^{th} grade track. In addition to the track subjects, students must take exams in compulsory core subjects that are the same for all students, regardless of track. After taking national exams, university applicants submit a list of their preferred tertiary degree programs to the Ministry of Education. Although students can apply to many degree programs from all high school tracks, some programs assign a higher weight to specific subjects when calculating the university admission score. (see https://eacea.ec.europa.eu/national-policies/eurydice/content/greece_en).

Figure 2: **Performance in STEM and Non-STEM Subjects in 10th Grade by Gender**



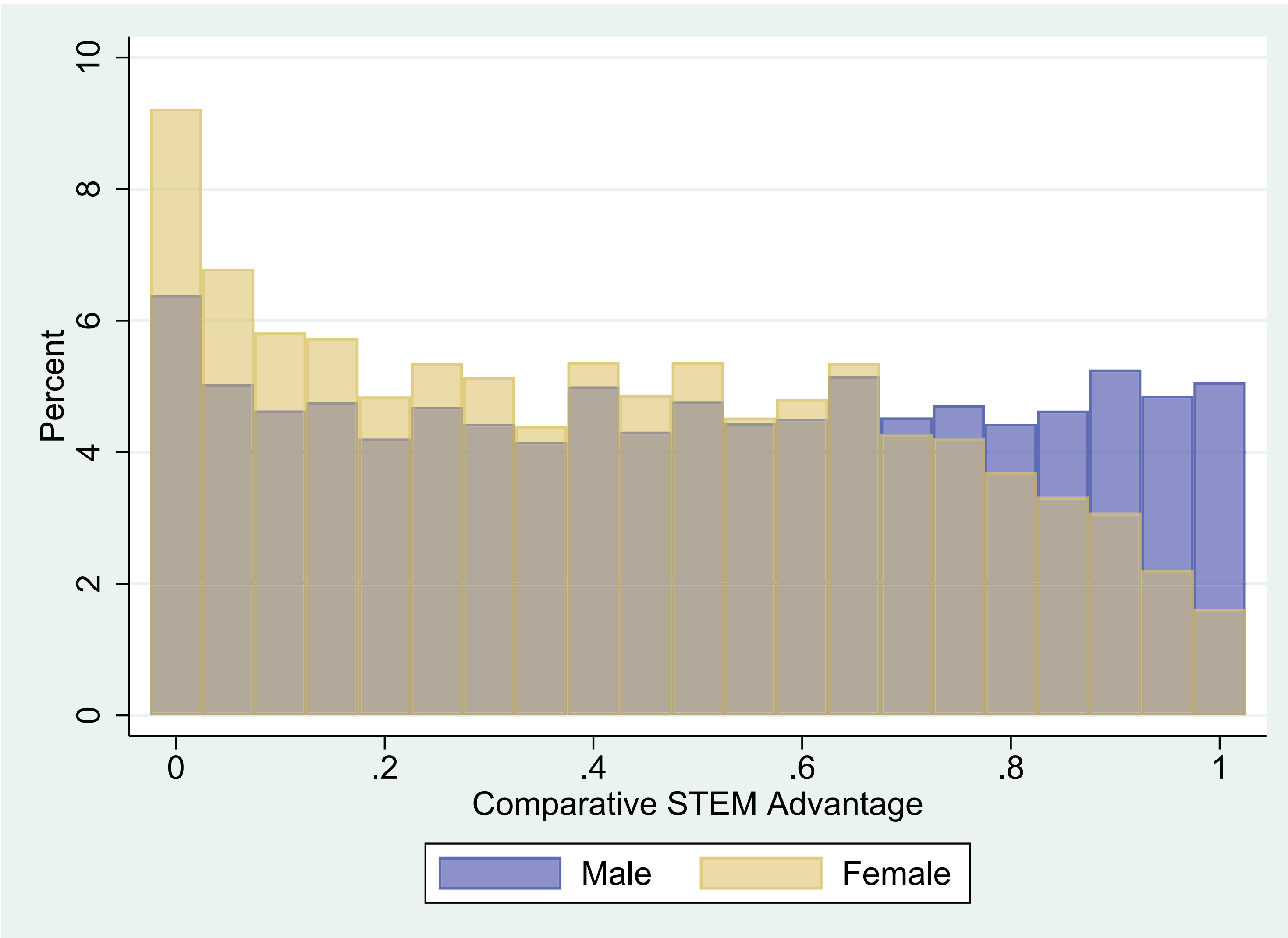
Notes: This graph displays the performance (out of 20) in six subjects, for males and females separately. Final exam scores are used to measure student performance. Females perform significantly better in almost every subject (except for Physics, where the difference is not statistically different from zero), but their performance advantage is even higher in non-STEM subjects (Modern Greek, Greek Literature, and Ancient Greek) compared with STEM subjects (Algebra, Chemistry, and Physics).

Figure 3: **Variation of Comparative STEM Advantage with Respect to STEM Advantage**



Notes: This graph shows the relation between students' absolute and comparative STEM advantages. For each value of absolute STEM advantage between 0.4 and 1.4, the box plot displays the median, the first quartile to third quartile (solid box), and the minimum and maximum of comparative STEM advantage.

Figure 4: **Differential Comparative STEM Advantage for Males and Females**

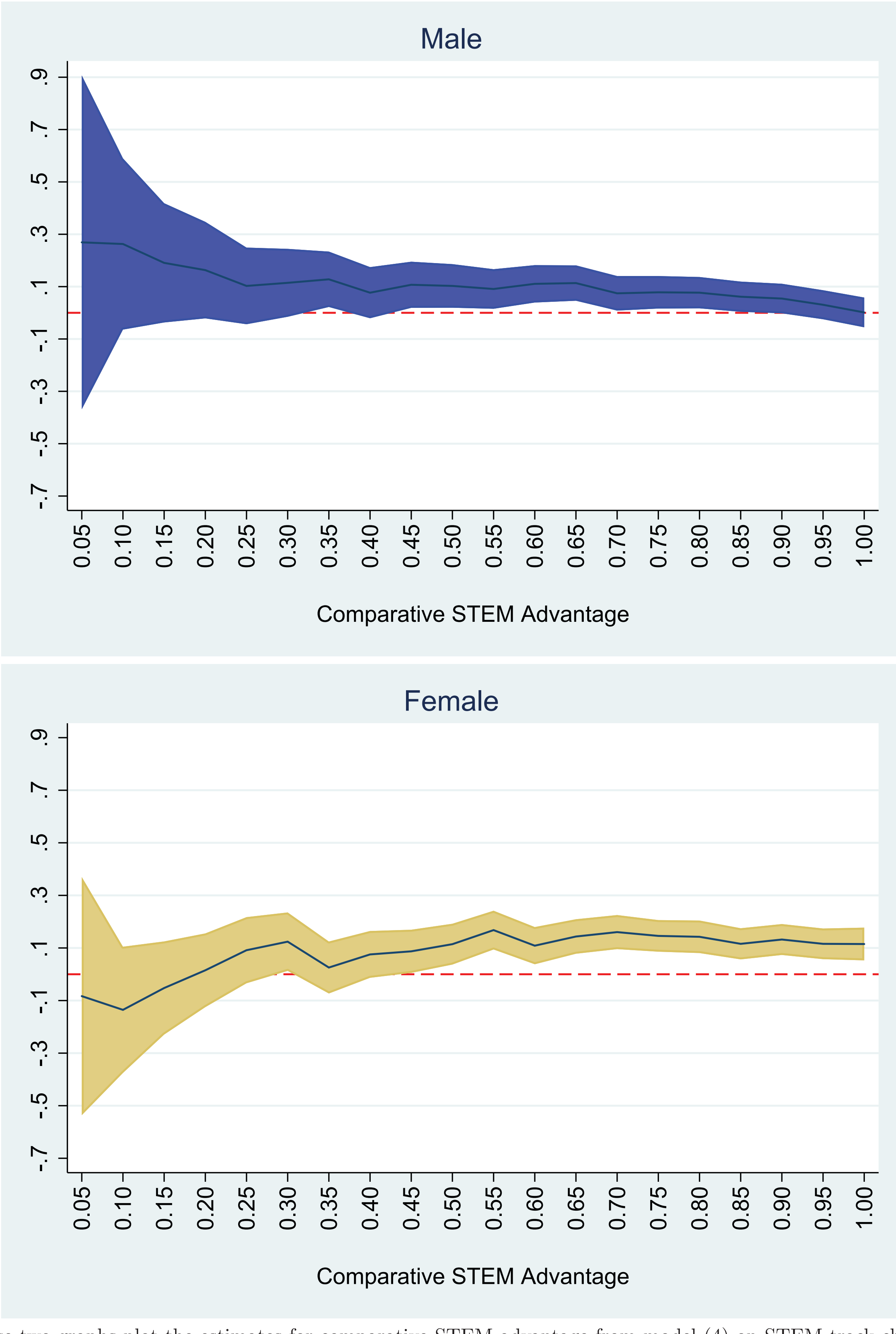


Notes: This figure shows the percentage of females and males in each percentile rank in STEM advantage. Females are much less likely than males to have a higher percentile rank in STEM advantage (i.e., comparative STEM advantage).

Figure 5: **Identifying Variation in Peers' Dispersion of Absolute STEM Advantage**

Notes: This figure illustrates the variation we exploit to identify the effect of *comparative* STEM advantage. Consider that there are two classrooms in school A, i.e., classroom 1 and classroom 2. Each vertical line represents a particular student's absolute STEM advantage position in the classroom performance distribution. Both classrooms have the same number of students and the same average absolute STEM advantage (indicated by the red vertical line). Classroom 1 has a higher dispersion of absolute STEM advantage than classroom 2. Two students with the same own absolute STEM advantage and the same average classroom characteristics (including average absolute STEM advantage) could have different comparative STEM advantage (proxied by the within-classroom rank position of absolute STEM advantage) because of different dispersion of peers' absolute STEM advantage in different classrooms due to random peer group formation.

Figure 6: **Nonlinear Effect of Comparative STEM Advantage by Gender**



Notes: These two graphs plot the estimates for comparative STEM advantage from model (4) on STEM track choice in grade 11 at various levels of comparative STEM advantage. The top graph reports the estimates only for males, and the bottom graph only for females.

Appendix

Descriptive Evidence of the Effect of STEM and non-STEM Performance

Panel A of Table A1 focuses on the subgroup of students who enroll in a non-STEM (columns 1 and 6) and STEM track in 11$^{\text{th}}$ grade (columns 2 and 7), separately. As shown in columns 1 and 2, males who enroll in a STEM track in 11$^{\text{th}}$ grade have a higher STEM performance but slightly lower non-STEM performance in 10$^{\text{th}}$ grade than males who go into non-STEM in 11$^{\text{th}}$ grade. The corresponding differences and p-values are shown in columns (3) and (4), respectively. Females who enroll in a STEM track in grade 11 (column 7) have a higher performance in both types of subjects compared with females who go into a non-STEM track (column 6). The corresponding differences in column (8) are both positive and statistically significant (column 9). Females going into STEM and non-STEM tracks have a higher performance in both types of subjects than males going into STEM and non-STEM tracks, respectively. The classroom average grade in STEM and non-STEM is very similar for males and females. Males and females who enroll into a STEM track have a higher absolute STEM advantage.

Panel B of Table A1 focuses on the subgroup of students who apply for a non-STEM (columns 1 and 6) and STEM university degree (columns 2 and 7), separately. Comparing columns (1) to (6) and (2) to (7), we find that females who apply to both types of degree programs outperform males in both types of subjects. Also, males and females who apply to a STEM degree program have a higher 10$^{\text{th}}$ grade performance in both types of subjects compared with those who do not apply to a non-STEM degree program. Differences in classroom average grades in the two types of subjects between the two groups of university applicants are small (0.305 and 0.193 for males in STEM and non-STEM, respectively, and 0.118 and 0.086 for females in STEM and non-STEM, respectively). Males and females who apply for a STEM university degree have a higher absolute STEM advantage.

Table A1: **Descriptive Statistics by Gender and Enrollment**

	Male				Female			
Panel A	Non-STEM Track Enrollment in Grade 11	STEM Track Enrollment in Grade 11	Diff.	*p-value*	Non-STEM Track Enrollment in Grade 11	STEM Track Enrollment in Grade 11	Diff.	*p-value*
	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)
Own Grade in STEM	8.019	11.088	3.069	0.000	9.035	12.528	3.494	0.000
Own Grade in non-STEM	12.787	12.414	-0.373	0.000	13.821	14.093	0.273	0.000
Comparative STEM Advantage	0.278	0.547	0.270	0.000	0.296	0.547	0.251	0.000
Class Av. Grade in STEM	10.084	10.286	0.202	0.000	10.115	10.319	0.204	0.000
Class Av. Grade in non-STEM	13.005	12.908	-0.098	0.000	12.918	12.892	-0.025	0.117
Own Absolute Adv. in STEM	0.622	0.891	0.269	0.000	0.645	0.884	0.240	0.000
Class Absolute Adv. in STEM	0.781	0.802	0.022	0.000	0.789	0.807	0.018	0.000
Obs	6,185	26,725			21,177	18,925		
Panel B	Non-STEM University Application	STEM University Application	Diff.	*p-value*	Non-STEM University Application	STEM University Application	Diff.	*p-value*
Own Grade in STEM	8.717	11.972	3.256	0.000	11.202	13.147	1.944	0.000
Own Grade in non-STEM	10.884	12.975	2.091	0.000	13.232	14.482	1.251	0.000
Comparative STEM Advantage	0.454	0.583	0.129	0.000	0.492	0.573	0.081	0.000
Class Av. Grade in STEM	10.063	10.368	0.305	0.000	10.241	10.359	0.118	0.000
Class Av. Grade in non-STEM	12.766	12.959	0.193	0.000	12.833	12.919	0.086	0.001
Own Absolute Adv. in STEM	0.799	0.926	0.126	0.000	0.840	0.906	0.066	0.000
Class Absolute Adv. in STEM	0.794	0.806	0.012	0.000	0.806	0.808	0.002	0.378
Obs	7,058	19,523			5,560	13,188		

Notes: This table shows summary statistics for student's own performance in STEM and non-STEM subjects in grade 10, classroom average performance in STEM and non-STEM subjects in grade 10, own and classroom absolute STEM performance in grade 10 for different subgroups by gender, separately. Panel A reports these statistics for students who enroll in a non-STEM and STEM tracks in grade 11 for males and females, separately. Panel B reports these statistics for students who apply for a non-STEM and STEM university degree for males and females, separately. Columns (3) and (8) report the differences and columns (4) and (9) report the p-values for the t-test on the difference between non-STEM and STEM enrollment.

The Effect of Absolute STEM Advantage

In this section, we examine empirically the following hypothesis: The higher an individual's competence in STEM relative to their competence in non-STEM, the more likely they are to specialize in STEM, while controlling for his/her peers' competence in STEM relative to non-STEM. Similarly, the higher a female student's peers' competence in STEM relative to non-STEM, the less likely she is to specialize in STEM, while keeping constant her competence in STEM relative to non-STEM.

An individual's competence in STEM relative to their competence in non-STEM can be proxied using definition (2). A similar definition can be used to proxy a student's peers' competence in STEM relative to non-STEM. We investigate the association between own and peer advantage in STEM using the following specification:

$$
\begin{aligned}
Y_{ijt} = {} & \beta_0 + \beta_1 \underbrace{\frac{Grade\_STEM_{ijt}}{Grade\_nonSTEM}_{ijt}}_{\text{STEM advantage}} + \beta_2 \underbrace{\frac{Av\_Classroom\_Grade\_STEM_{ijt}}{Av\_Class\_Grade\_nonSTEM}_{ijt}}_{\text{Classroom STEM advantage}} \\
& + \mu_{st} + \varepsilon_{ijt}
\end{aligned} \tag{A1}
$$

Table A2 presents our estimates of model (A1). Higher (absolute) STEM advantage increases the likelihood to enroll in a STEM track in grade 11. Moreover, (absolute) STEM advantage is positively correlated with the likelihood of applying for a STEM university degree program.

Table A2: **Association between Students' Own and Classroom STEM Advantage on Future Study Decisions**

	STEM Track in Grade 11		Applied for STEM University Degree	
	(1)	(2)	(3)	(4)
Female	-0.287***	-0.433***	-0.024***	0.037
	(0.004)	(0.024)	(0.005)	(0.027)
Abs. STEM Advantage	0.652***	0.448***	0.274***	0.285***
	(0.008)	(0.009)	(0.011)	(0.012)
Abs. STEM Advantage × Female		0.430***		-0.035**
		(0.012)		(0.018)
Class Abs. STEM Advantage	-0.299***	-0.173***	-0.081***	-0.064**
	(0.025)	(0.029)	(0.028)	(0.031)
Class Abs. STEM Advantage × Female		-0.245***		-0.037
		(0.031)		(0.036)
Obs.	72,943	72,943	45,269	45,269
School x Year FE	Yes	Yes	Yes	Yes
Controls	No	No	No	No
Mean Y	0.63	0.63	0.72	0.72
St. Dev Y	0.48	0.48	0.45	0.45
Raw Gender Gap Y	-0.34	-0.34	-0.03	-0.03

Notes: This table examines the patterns of track choice in grade 11 and university departments application. Importantly, the table has no intent to identify causal inference, but rather questions whether the gender gap in STEM enrollment can be explained by gender difference in student performance. The table reports the results of a specification in which the track enrollment and university application decisions of student i, in school j, cohort t are regressed on their own and classmates' average absolute STEM advantage, school-by-cohort FE, and student's characteristics, such as gender and year of birth. Each regression includes school-cohort FE. Standard errors are clustered at the school-cohort level. The last row in each panel shows the slope coefficient of the regression of each outcome variable on a female indicator, reflecting the gender gap in that outcome. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A3: **Association between Cardinal Comparative STEM Advantage and Future Study Decisions**

	STEM Track in Grade 11		Applied for STEM University Degree	
	(1)	(2)	(3)	(4)
Cardinal Comparative STEM Adv.	0.499***	0.346***	0.209***	0.217***
	(0.006)	(0.007)	(0.008)	(0.009)
Cardinal Comparative STEM Adv. × Female		0.317***		-0.024*
		(0.010)		(0.014)
Obs.	72,940	72,940	45,259	45,259
Classroom FE	Yes	Yes	Yes	Yes
Controls	No	No	No	No
Mean Y	0.63	0.63	0.72	0.72
St. Dev Y	0.48	0.48	0.45	0.45
Raw Gender Gap Y	-0.34	-0.34	-0.03	-0.03

Notes: This table explores the patterns of track choice in grade 11 and university department application. Importantly, the table has no intent to identify causal inference, but rather questions whether the gender gap in STEM specialization can be explained by gender differences in student performance. The table reports the results of a specification in which the track enrollment and university application decisions of student i, in classroom j, in school s, in cohort t are regressed on their cardinal comparative STEM advantage (as defined in the LHS of equation (1)). The regression includes classroom FE and student's characteristics, such as gender and year of birth. Standard errors are clustered at the school-cohort level. The last row in each panel shows the slope coefficient of the regression of each outcome variable on a female indicator, reflecting the gender gap in that outcome. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Dealing with Possible Sample Selection

In order to deal with possible bias caused by sample selection, we employ an Inverse-probability-weighted estimator for model (4). In particular, we assume that the process that causes some of the data to be missing is a function of observable covariates and a random process that is independent of the outcome. First, we formally test which observable students or class's characteristics are correlated with attrition, by estimating a probit model for attrition. Perhaps not surprisingly, attrition is correlated with student performance in STEM and non-STEM subjects, as well as students' STEM advantage. Additional variables that are significant predictors of attrition are the dummy for female, the interaction between non-STEM average performance and female, and average classroom performance in STEM and non-STEM subjects. Chi-square statistics for the Wald test of whether these variables are jointly equal to zero is 757.64, suggesting that these variables are jointly statistically different from zero at the highest level of significance. In other words, these variables are significant predictors of students' transfer out.

Given that the transfer-out rate may be non-random, we compute the inverse probability weights for Model (4) to correct for attrition. We compute the predicted probabilities and the inverse probability weights from the restricted probit. Intuitively, this procedure gives higher weight to students with characteristics similar to those of students who subsequently transfer out. Table A6 shows the main result for our model when attrition is not controlled for and when it is controlled. The results remain largely unaffected.

Table A4: **Gender Difference in Early Leavers and Students' Attrition Rate**

	Male	Female	Difference	*p-value*
	(1)	(2)	(3)	(4)
Early leavers	0.082	0.043	-0.039	0.000
Students' attrition	0.172	0.133	-0.039	0.000

Notes: This table reports male and female early leavers and attrition rate (in columns 1 and 2 respectively). Column 3 reports gender differences in early leavers and student attrition. Column 4 reports the p-value for the t-test on the gender difference.

Table A5: **Association between Classroom Performance and Gender Difference in Sample Attrition**

	GD Early Leavers	GD Students' Attrition
	(1)	(2)
Classroom GPA	-0.272	-0.029
	(0.195)	(0.223)
Obs.	3,428	3,428
School x Year FE	Yes	Yes

Notes: This table reports results of the estimated effects of the classroom average GPA on two types of attrition. Column (1) shows results of the estimated effect of classroom average GPA on the gender difference (GD, male minus female) in early leavers in each classroom. We define *early leavers* as those students who do not complete grade 10, but drop out from school early during their 10^{th} grade. Column (2) shows results of the estimated effect of classroom average GPA on the gender difference (GD) in students' attrition in each classroom. We define *attriters* as students who leave the sample at the end of 10^{th} grade after they complete grade 10. The unit of observation is the classroom. Clustered standard errors at the school level are reported in parentheses.

Table A6: **The Effect of Comparative STEM Advantage on STEM track in Grade 11, without and with IPWs**

	Without Attrition Weights		With Attrition Weights	
	Quadratic	Nonlinear	Quadratic	Nonlinear
	(1)	(2)	(3)	(4)
Comparative STEM Advantage	0.038*	0.030	0.073***	0.047*
	(0.020)	(0.021)	(0.024)	(0.026)
Comparative STEM Advantage × Female	0.202***	0.161***	0.182***	0.139***
	(0.022)	(0.022)	(0.025)	(0.025)
Obs.	72,940	72,940	72,865	72,865
School × Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean Y	0.63	0.63	0.63	0.63
St. Dev Y	0.48	0.48	0.48	0.48

Notes: This table reports OLS estimates for model (4), without correcting for attrition (columns 1 and 2), and using inverted probability weights to account for attrition (columns 3 and 4). In each regression, the dependent variable is a dummy for whether the student applies to a STEM track at the end of grade 10. The first specification includes a quadratic term for STEM advantage and the second specification includes 10 dummies for different levels of absolute STEM advantage. Each regression controls for student gender, absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and classroom FE. Standard errors are clustered at the school-cohort level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A7: **The Effect of Comparative STEM Advantage on University Application using Different Definitions of STEM Departments**

	Linear (1)	Quadratic (2)	Cubic (3)	Quartic (4)	Quintic (5)	Nonlinear (6)
	STEM departments = Sciences, Engineering, and Technology					
Comparative STEM Advantage	0.070***	-0.040	-0.046*	-0.040	-0.033	-0.014
	(0.024)	(0.026)	(0.026)	(0.027)	(0.027)	(0.028)
Comparative STEM Advantage × Female	0.093***	0.111***	0.112***	0.110***	0.108***	0.102***
	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Obs.	45,259	45,259	45,259	45,259	45,259	45,259
Mean of Y	0.72	0.72	0.72	0.72	0.72	0.72
St. Dev. Y	0.45	0.45	0.45	0.45	0.45	0.45
Raw Gender Gap Y	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
	STEM departments = Sciences, Engineering, Technology, Economics, and Business					
Comparative STEM Advantage	0.114***	-0.005	0.001	-0.011	-0.011	0.008
	(0.021)	(0.022)	(0.023)	(0.024)	(0.024)	(0.024)
Comparative STEM Advantage × Female	0.128***	0.174***	0.153***	0.147***	0.147***	0.142***
	(0.023)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)
Obs.	72,940	72,940	72,940	72,940	72,940	72,940
Mean of Y	0.55	0.55	0.55	0.55	0.55	0.55
St. Dev. Y	0.50	0.50	0.50	0.50	0.50	0.50
Raw Gender Gap Y	-0.22	-0.22	-0.22	-0.22	-0.22	-0.22
	STEM departments = Sciences, Engineering, Technology, and Health Science					
Comparative STEM Advantage	0.133***	0.065***	0.056**	0.041	0.040	0.045*
	(0.022)	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)
Comparative STEM Advantage × Female	0.110***	0.146***	0.127***	0.126***	0.125***	0.121***
	(0.023)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)
Obs.	72,940	72,940	72,940	72,940	72,940	72,940
Mean of Y	0.61	0.61	0.61	0.61	0.61	0.61
St. Dev. Y	0.49	0.49	0.49	0.49	0.49	0.49
Raw Gender Gap Y	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07
Classroom FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports OLS estimates for model (4) for application to university STEM departments, using broader definitions of STEM departments. Panel A uses displays the effect using the same definition of STEM used in the main analysis for comparison purposes. Panel B displays the results when Economics and Business departments are included in the definition of STEM. Panel C shows the results when Health Science departments are included in the STEM definition. In each panel, we show several specifications for different degrees of polynomials for STEM advantage (columns 1-5) as well as a nonlinear specification that uses dummy variables for each decile of rank (column 6). Each regression controls for student gender, absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and classroom FE. Standard errors are clustered at the school-cohort level. The last row in each panel shows the slope coefficient of the regression of each outcome variable on a female indicator, reflecting the gender gap in that outcome. Each regression controls for student STEM performance, non-STEM performance, and absolute STEM advantage. Each regression includes classroom FE. Standard errors are clustered at the school-cohort level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A8: **The Effect of Comparative STEM Advantage on STEM Track Choice in 11th Grade, using Different Definitions of STEM Subjects**

	STEM Track in Grade 11			
	(1)	(2)	(3)	(4)
Comparative STEM Advantage	0.030			
	(0.021)			
Comparative STEM Advantage × Female	0.161***			
	(0.022)			
Comparative STEM Advantage (STEM=Algebra)		0.044**		
		(0.021)		
Comparative STEM Advantage (STEM=Algebra) × Female		0.152***		
		(0.023)		
Comparative STEM Advantage (STEM=Chemistry)			0.050**	
			(0.021)	
Comparative STEM Advantage (STEM=Chemistry) × Female			0.151***	
			(0.021)	
Comparative STEM Advantage (STEM=Physics)				0.050**
				(0.021)
Comparative STEM Advantage (STEM=Physics) × Female				0.110***
				(0.022)
Obs.	72,940	72,940	72,940	72,940
Classroom FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: This table reports OLS estimates for model (4), using different definitions of STEM advantage. In column (1) STEM is defined as the average of Algebra, Chemistry, and Physics; in column (2) STEM is defined as performance only in Algebra; in column (3) STEM is defined as performance only in Chemistry; in column (4) STEM is defined as performance only in Physics. The non-STEM subjects average performance is always defined as average performance in Modern Greek, Greek Literature, and Ancient Greek. In each regression the dependent variable is a dummy indicating whether the student applied to a STEM track at the end of grade 10. Each regression controls for student gender, a second-order polynomial of absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and classroom FE. Standard errors are clustered at the school-cohort level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A9: **The Effect of Comparative Non-STEM Advantage on Future Study Decisions**

	STEM Track in Grade 11		Applied for STEM University Degree	
	Quadratic	Non Linear	Quadratic	Non Linear
	(1)	(2)	(3)	(4)
Comparative non-STEM Adv.	-0.025	-0.035	-0.045	-0.014
	(0.021)	(0.023)	(0.028)	(0.031)
Comparative non-STEM Adv. × Female	-0.168***	-0.113***	-0.058	-0.044
	(0.030)	(0.034)	(0.045)	(0.048)
Obs.	72,940	72,940	45,259	45,259
Classroom FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean Y	0.63	0.63	0.72	0.72
St. Dev Y	0.48	0.48	0.45	0.45
Raw Gender Gap Y	-0.34	-0.34	-0.03	-0.03

Notes: This table reports the OLS estimates for model (4). Rank in non-STEM advantage is used rather than rank in STEM advantage. For each of the two outcomes (grade 11 STEM track choice and application to STEM degree program), two specifications are considered. Columns 1 and 3 show the effect of comparative non-STEM advantage, while columns 2 and 4 report the interaction term between comparative non-STEM advantage and the dummy for female. Each regression controls for student gender, absolute STEM advantage, STEM, non-STEM performance, interactions of individual terms with gender, and classroom FE. Standard errors are clustered at the school-cohort level. The last row in each panel shows the slope coefficient of the regression of each outcome variable on a female indicator, reflecting the gender gap in that outcome. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Using Performance in the First Semester of 10^{th} Grade

In this section, we employ performance in the first semester of 10^{th} grade to compute students' absolute and comparative STEM advantage. Students are allocated to classrooms at the beginning of grade 10. Therefore, a student's final exam scores at the end of the year, which determine their comparative STEM advantage, could be affected by peer effects. In our main analysis, this problem is mitigated by the fact that classroom average performance is controlled for through classroom FE. Nevertheless, we decided to use performance during the first semester in grade 10, as robustness check. Table A10 shows the summary statistics when performance in the first semester of 10^{th} grade is used. Figure A7 shows the performance in the first semester of 10^{th} grade for males and females in Algebra, Physics, Chemistry, Modern Greek, Greek Literature, and Ancient Greek. Table 8 reports the estimates of our main model using first-semester performance. The results remain robust.

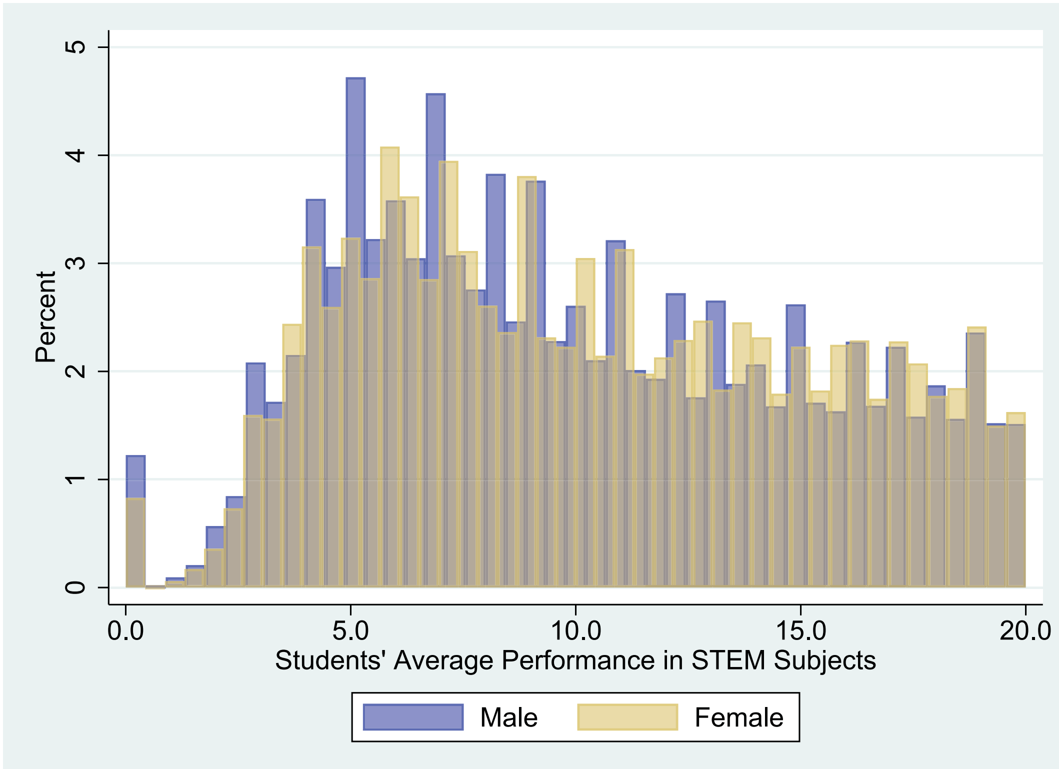
Table A10: **Descriptive Statistics: Using Performance in First Semester 10^{th} Grade**

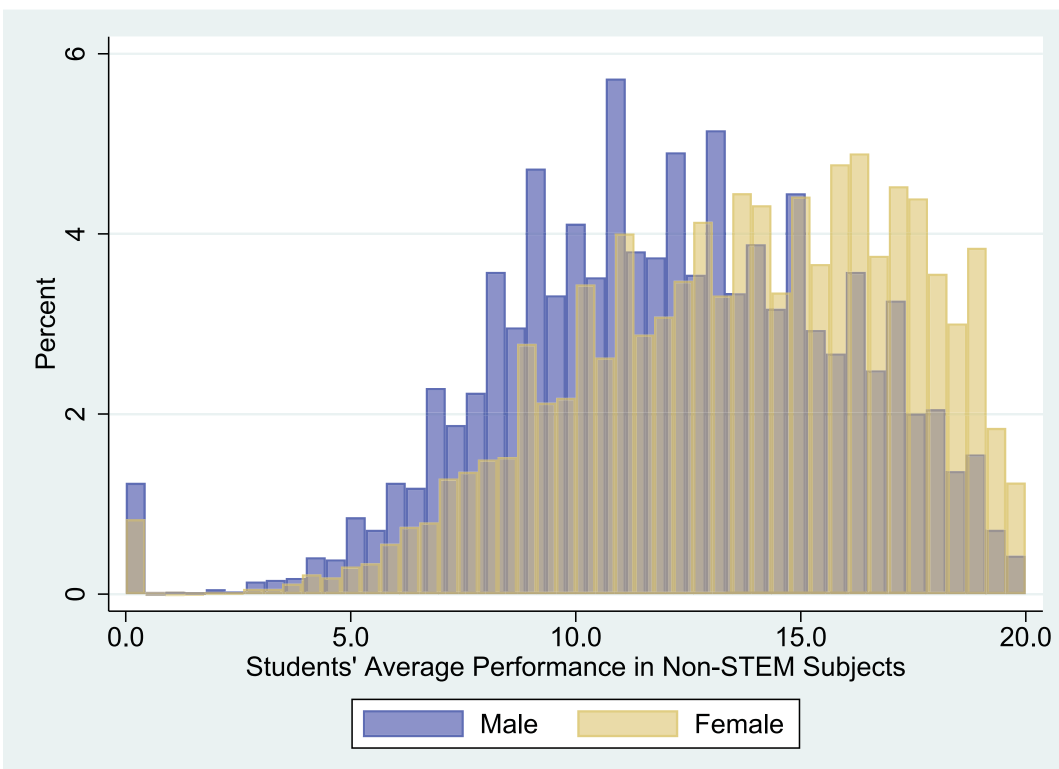
	Male	Female	Difference	*p-value*
	(1)	(2)	(3)	(4)
Panel A: Performance in Grade 10				
Algebra	14.078	14.556	0.478	0.000
Physics	14.277	14.591	0.314	0.000
Chemistry	14.594	15.144	0.550	0.000
Modern Greek	13.891	15.057	1.166	0.000
Greek Literature	14.378	15.807	1.429	0.000
Ancient Greek	13.891	15.214	1.323	0.000
Panel B: Constructed variables in Grade 10				
Own Grade in STEM	14.315	14.763	0.448	0.000
Own Grade in non-STEM	14.052	15.357	1.305	0.000
Class Average Grade in STEM	14.541	14.565	0.024	0.001
Class Average Grade in non-STEM	14.754	14.761	0.007	0.346
Comparative STEM Advantage	0.456	0.316	-0.140	0.000

Notes: This table reports the gender differences in performance for the six subjects we use to construct our variable in grade 10 (Panel A) and the gender differences for the variable we construct and we use for our analysis (Panel B). The fourth column reports p-values for the t-test on the gender difference on each variables.

Appendix Figures

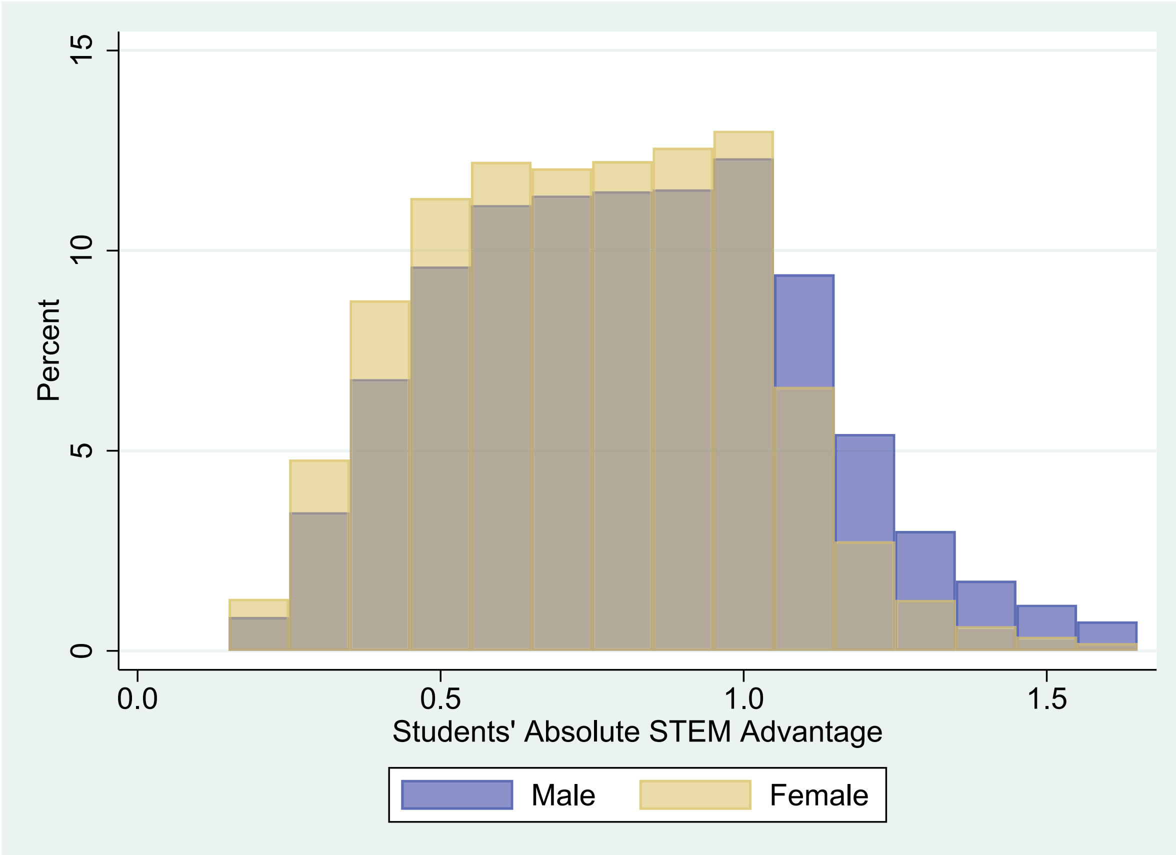
Figure A1: **Distribution of Performance in STEM and Non-STEM Subjects at the End of 10^{th} Grade**





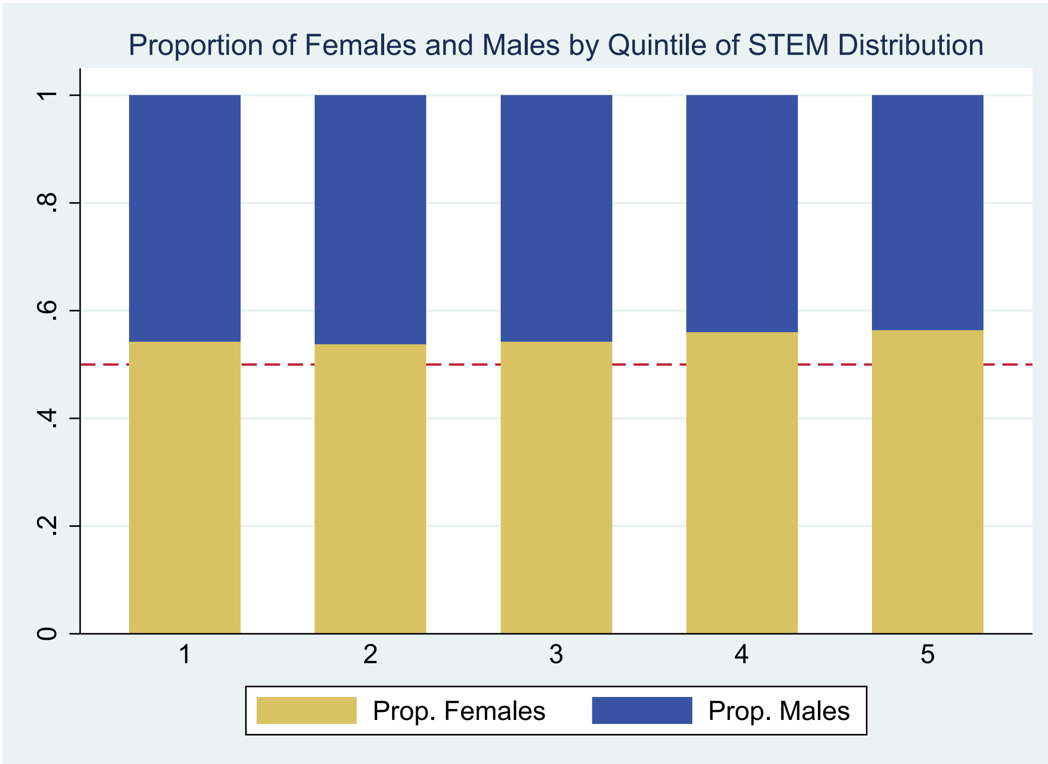
Notes: These two graphs plot the distributions of performance at the end of 10^{th} grade for STEM subjects (Mathematics, Physics, and Chemistry) in the first graph and non-STEM subjects (Modern Greek, Ancient Greek, and Greek Literature) in the second graph.

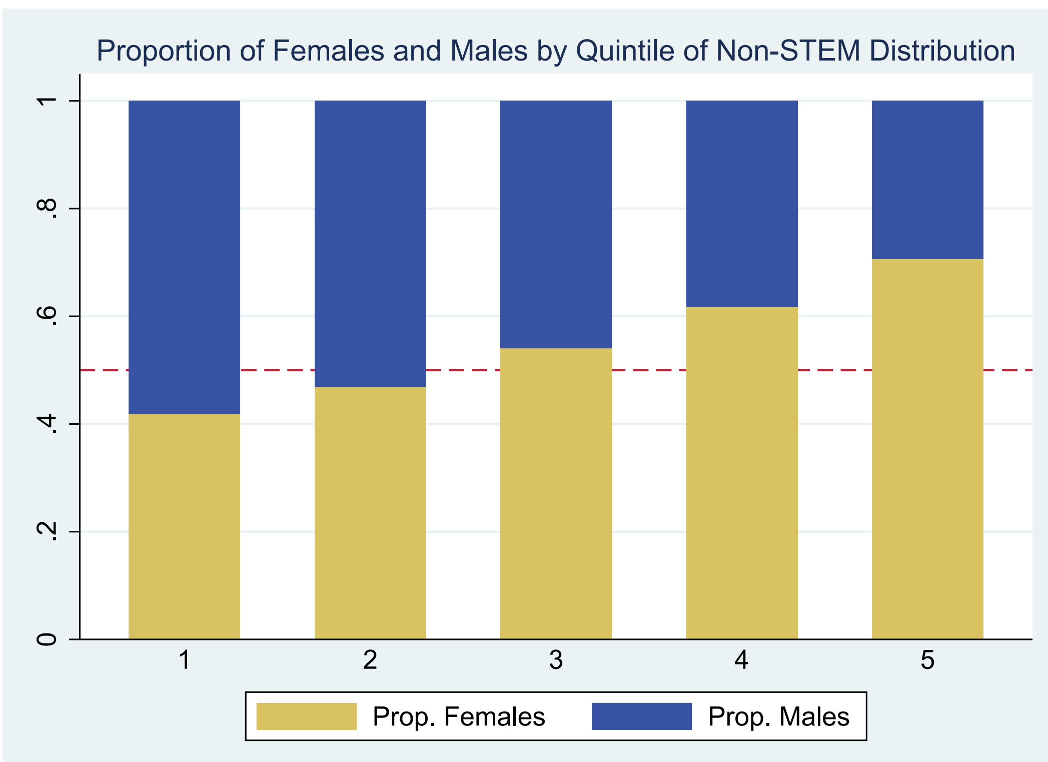
Figure A2: **Distribution of Absolute STEM Advantage at the End of 10th Grade**



Notes: This graph plots the distribution of absolute STEM advantage at the end of grade 10 for males and females.

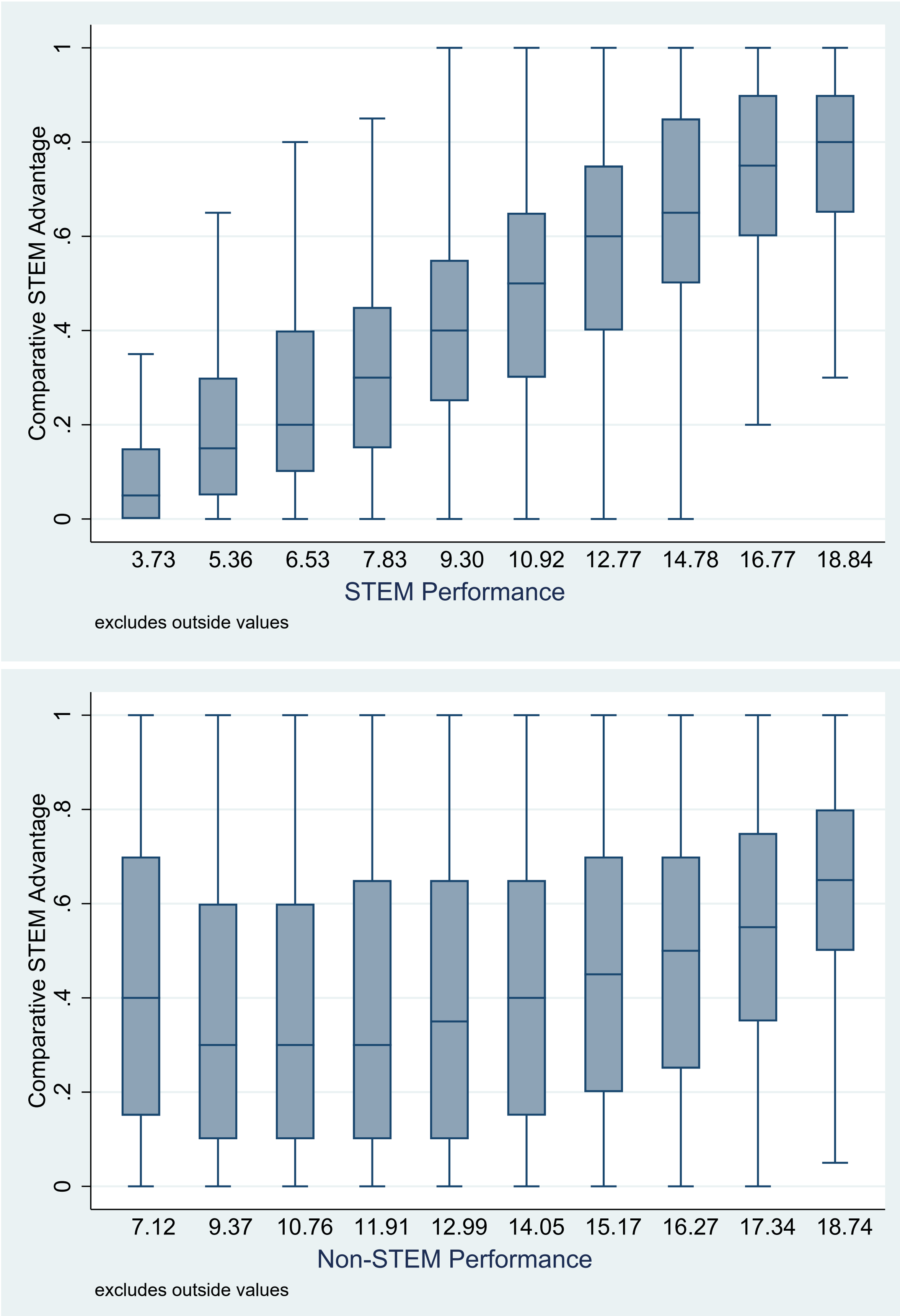
Figure A3: **Proportion of Males and Females by Quintile of STEM/Non-STEM Performance Distribution**





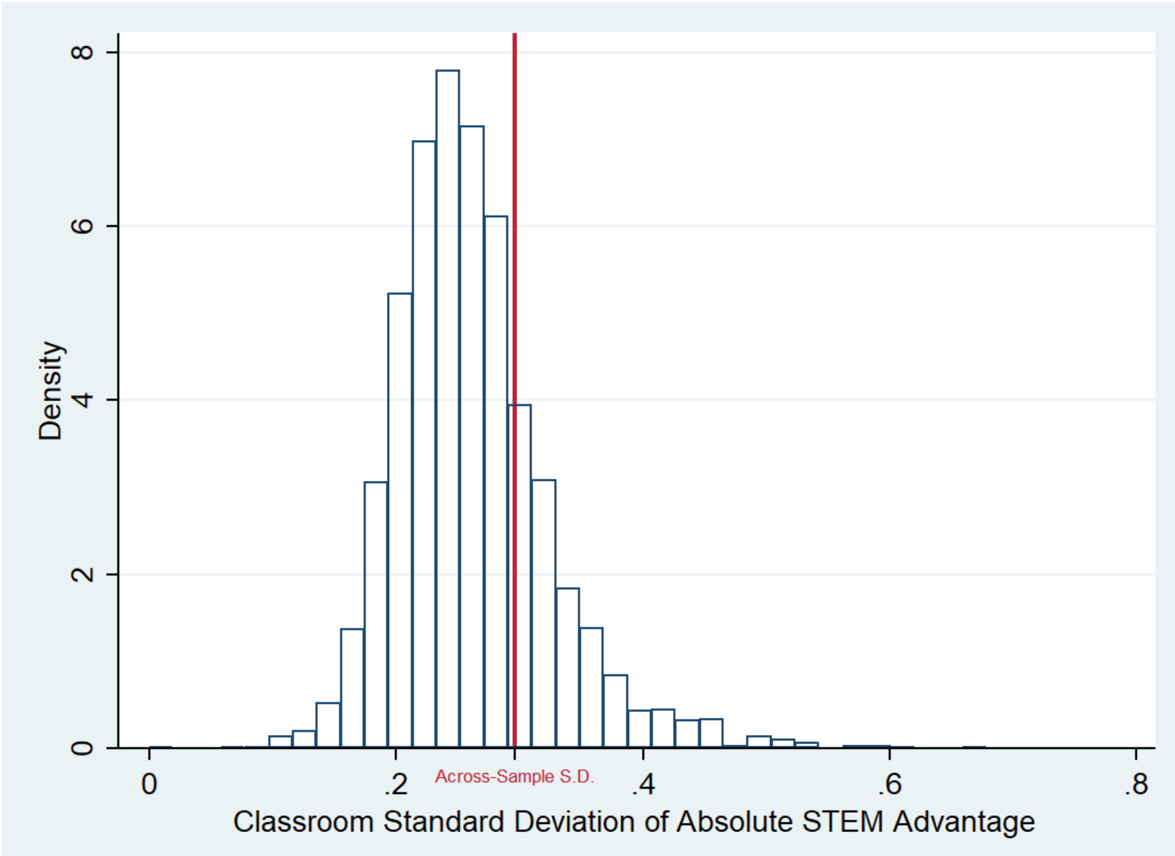
Notes: These two figures show the proportion of students by quintiles of the STEM and non-STEM performance distribution at the end of grade 10. STEM ability is computed as average GPA in Algebra, Physics, and Chemistry. Non-STEM performance is computed as average GPA in Modern Greek, Greek Literature, and Ancient Greek. While the proportion of females is constant across the quintile of STEM performance distribution, a greater number of female are in the top quintiles of the non-STEM performance distribution. The dotted red line is drawn at 0.5 to show the equal representation of gender as benchmark.

Figure A4: **Variation of Comparative STEM Advantage with Respect to STEM and Non-STEM Performance**



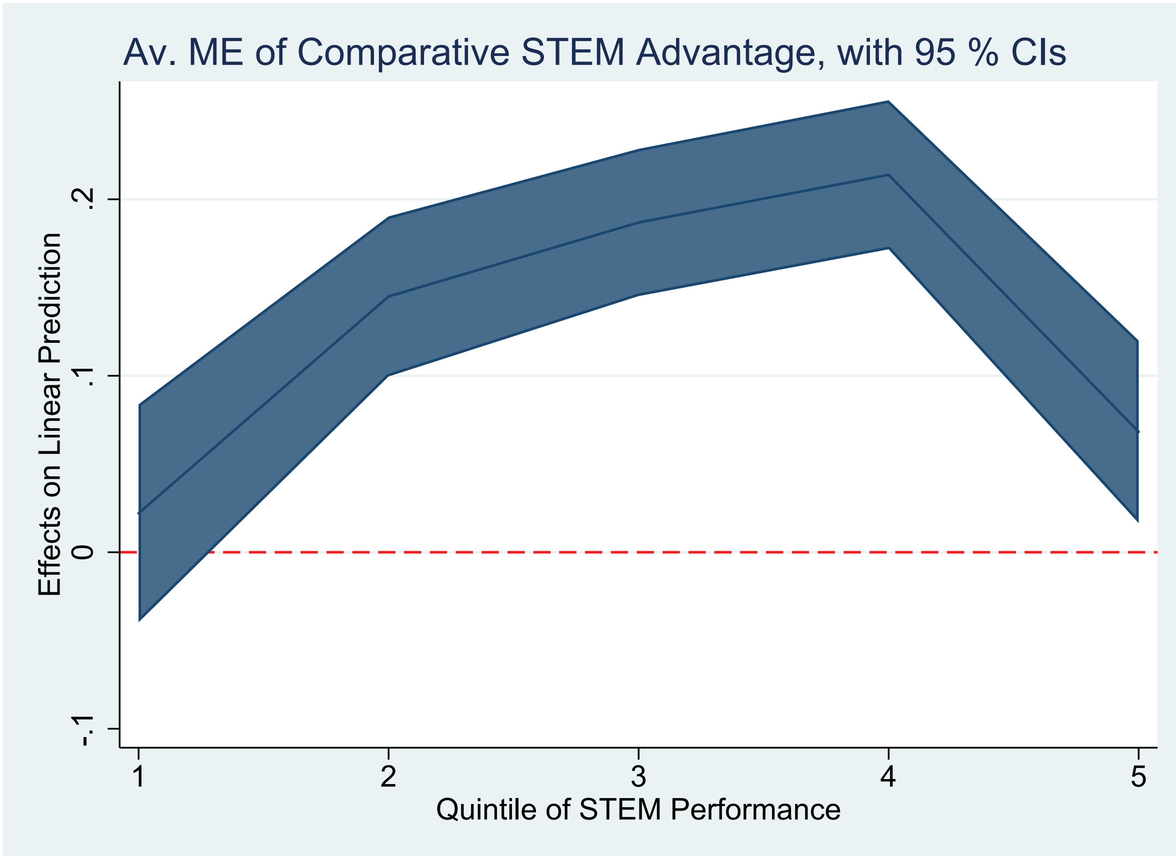
Notes: These two box plots show the variation in rank in STEM advantage by decile of STEM and non-STEM performance at the end of grade 10.

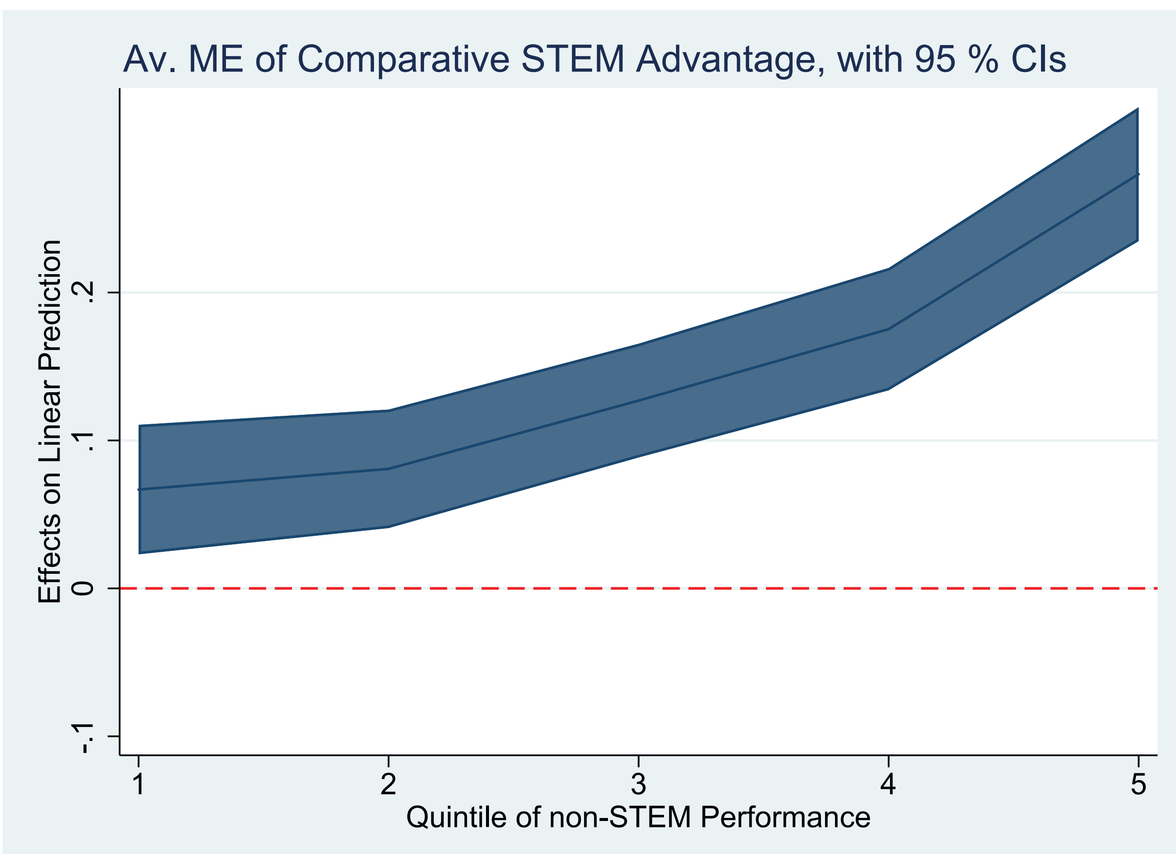
Figure A5: **Distribution of Dispersion of Absolute STEM Advantage within Classrooms**



Notes: The histogram of within-classroom standard deviation of absolute STEM advantage reveals substantial variation in the dispersion of absolute STEM advantage in the classroom. The vertical line corresponds to the standard deviation of absolute STEM advantage across all students.

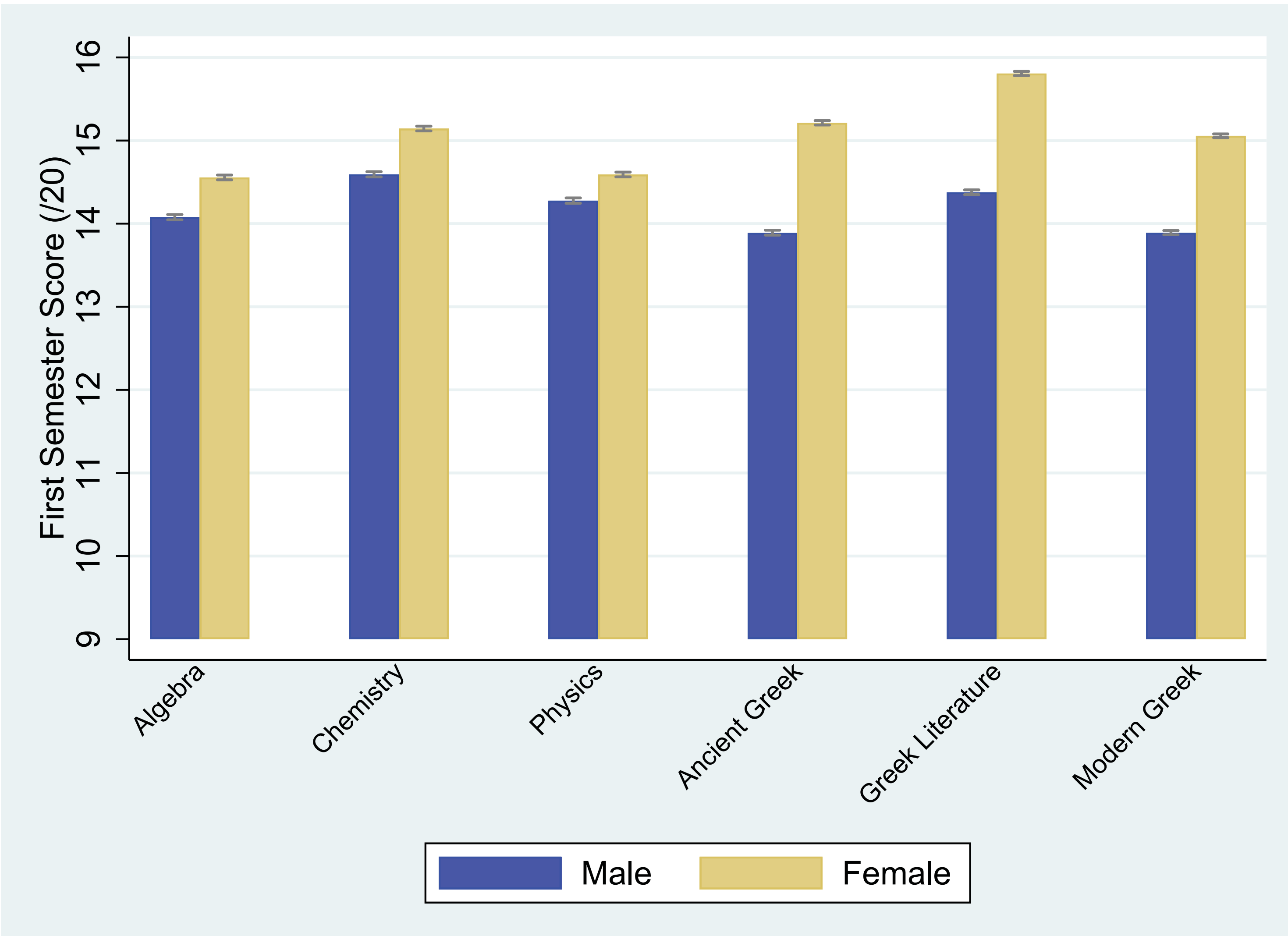
Figure A6: **Differential Effect of Comparative STEM Advantage across Different Quintiles STEM and Non-STEM Performance**





Notes: These two graphs plot the estimates for rank in STEM advantage as in model (4), on STEM track choice in grade 11, for each quintile of the STEM and non-STEM ability distribution. Both models include a quadratic polynomial for absolute STEM advantage. Standard errors are clustered at the school-cohort level.

Figure A7: **Performance in STEM and Non-STEM Subjects in 10th Grade by Gender**



Notes: The graph displays the performance in six subjects for males and females. Females perform significantly better in almost every subject, but their advantage is higher in non-STEM subjects (Modern Greek, Greek Literature, and Ancient Greek).

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