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ABSTRACT

Comparative Advantage and Gender Gap in STEM*

Why are females compared to males both more likely to have strong STEM-related performance and less likely to study STEM later on? We exploit random assignment of students to classrooms in Greece to identify the impact of comparative advantage in STEM relative to non-STEM subjects on STEM specialization decisions. We approximate comparative STEM advantage using the within-classroom ranking of the ratio of early-high school performance in STEM over non-STEM subjects. We find that females who are assigned to classroom peers among which they have a higher comparative STEM advantage are more likely to choose a STEM school track and apply to a STEM degree. Comparative STEM advantage appears irrelevant for males. Our results suggest that comparative STEM advantage explains at least 12% of the under-representation of qualified females in the earliest instance of STEM specialization. We discuss the mechanisms that amplify the role of comparative STEM advantage in STEM study.

JEL Classification: I21, I24, J24

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

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1 Introduction

It has been established that males are more likely to take mathematically oriented courses in school and obtain bachelor's degrees in computer sciences, engineering, physical sciences, and mathematics disciplines compared to females (National Science Foundation, 2016, 2017). Do we observe these differences because females perform poorly in mathematics and physics in school? The answer is negative. In fact, the under-performance of women in mathematics and physics tests has narrowed or even reversed in many countries, although the gender gaps in STEM university enrollment still remain. 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 under-representation of women in STEM disciplines (Ceci et al., 2014).

There is still a debate about what shapes gender differences in field and occupation specialization, while existing studies highlight the role of biological, social, psychological, and environmental factors that might influence this gap (Benbow, 1988; Waber, 1976; Steele, 1997; Lavy and Megalokonomou, 2019). On top of those factors, students may also be likely to make course taking and degree specialization decisions based 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 study how the relative comparison of one's own academic strengths and weaknesses with respect to her classmates affects a student's 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 rely mainly on analytical skills. Students might make different time investment and specialization decisions depending on their relative performance in one group of subjects compared to another.

We first investigate whether there exists a gender performance gap in these two types of compulsory subjects, STEM and non-STEM, and then we construct a measure of *absolute STEM*

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

[2] This distinction is of high interest, since there is under-representation 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).

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 of subjects (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 to 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 at specialization track at the end of the 10^{th} grade. This is the first opportunity students get 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 in the beginning of high school (10^{th} grade) are quasi-randomly (alphabetically based on surname) assigned to classrooms. Student stay for all courses with the same classmates 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 due to repeated interactions with their classmates and their 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 to 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 to 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 performances, but they 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 highlight 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 two descriptive evidence of the literature: (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 find that females have a lower comparative STEM advantage among quasi-random classmates than males. Second, we exploit random variation in one'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 into 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 two 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 to apply for a STEM degree at the university of around 1% for females, while males are not affected. We also find 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 the 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 under-representation of females in STEM disciplines.

We conduct a series of robustness exercises to provide further support to 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 non-linear functional form for absolute STEM advantage, but the results remain 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 a different attrition behavior. Our results remain similar when we account for attrition weights in the main specification (inverse attrition

[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.

weights). Third, we use student performance measured in different times and find that our results remain qualitatively unaffected. Forth, we show that our results are robust when we use a different STEM definitions for subjects and degree programs.

Our study moves beyond the existing literature 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 in 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 to the other, by using the rank in STEM relative to non-STEM performance within the classroom. The research design in recent works does not incorporate within-individual skill comparison (Elsner and Isphording, 2017; Murphy and Weinhardt, 2018; Elsner et al., 2018; Delaney and Devereux, 2019).

Secondly, 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-cohorts 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 random variation of students' abilities in classrooms within the same cohort and school, to account for cohort selection bias. The ideal research design to disentangle the effects of within-individual and across-individual comparisons would require identical students to be randomly assigned to peer groups. Those peer groups need to have the same group characteristics, but different ability distributions, which would result in students standing in different ranked positions in their peer group distribution. The alphabetical assignment of students to peer groups that we exploit in this paper resemble the ideal quasi-experiment.

[5] Some biological explanations have been proposed regarding the higher performances of males in STEM compared to non-STEM subjects in some countries, and their higher propensity to enroll in STEM related disciplines. The main research in this area includes analysis on 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).

The third contribution of our study relates to the broad external validity of our findings. Our study is the first one that explores social comparisons using the full support of the ability distribution. Unlike Elsner et al. (2018) who explore social comparisons at one Dutch business school, our results draw from a broader range of the ability distribution. We consider students before specializing in different fields 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 females 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 at a higher extend compared to males. Females may perceive lower grades as confirmation of stereotypes that females may not be 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 groups 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 within the same individual as well as between individuals may influence student 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 to attribute negative feedback to their own low ability than male students (Dweck et al., 1978). Also, Rask and Tiefenthaler (2008) highlight that women have a greater grade reliance, especially with respect to STEM-related subjects, while a negative feedback may simply bolster up and confirm their negative stereotypes. Steele (1997) discuss how women in quantitative fields encounter stereotype threats which 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 (1983)'s expectancy value theory, supported by the empirical evidence from the US by Wang et al. (2013) and Gardner (2016), suggests that students use their own relative performance to evaluate their academic strengths and consequently decide on STEM-related study decisions. At the same time, Zafar (2011); Bobba and Frisancho (2016) identify social comparison as a crucial driver for study 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 under-representation of qualified individuals in occupations associated with those skills.

Suppose that 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 related to this specialization intensively. 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 non-monetary returns, p_i^k, that 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 non-monetary return, associated with idiosyncratic preference for specialization k, takes a scalar form. The non-monetary return, p_i^k, represents the individual i's preference for specialization k, which could reflect, inter alia, non-pecuniary 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 competence of others in the same discipline.[8] For simplicity, assume that each individual is small enough compared to the labor market, so that their decision to follow a k specialization and consequently a k-related occupation will not influence the market competence α^k_{-i} or the 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 that 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 student general population and thus may not know how their own academic strengths compare to those of everyone else. Students may instead use a proxy an estimate of how their strengths compare to 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 relating to STEM specialization to be tested empirically: the fewer *others* (contenders) there are

[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.

that outperform an individual in terms of competence in STEM relative to non-STEM, the more likely that individual is to specialize in STEM, ceteris paribus. We investigate this hypothesis is 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 spans between 2001 and 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 the administrative records that include post-secondary 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 geographical 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 attended by all students from grade 10 to grade 12. We approximate

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

[10]Families have no room for enrolling their children into a different public school than the one assigned, as 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 concept of individual competence in STEM relative to non-STEM, presented in section 2, using the ratio between average scores in STEM over non-STEM subjects for each student. Thus, we define absolute STEM advantage[12] as follows:

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

The first instance students have to choose a specialization track is between the end of the 10$^{\text{th}}$ and the beginning of the 11$^{\text{th}}$ grade. The available tracks are Classics, Science, and Information Technology. Each track requires students to 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$^{\text{th}}$ and the beginning of the 12$^{\text{th}}$ grade.[13] Figure 1 shows the timeline of the choices high school students face. We categorize Classics track as a non-STEM track, while we categorize Science and Information Technology tracks as STEM tracks. There is no minimum performance threshold for students to enroll in any track. All schools offer these 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 the 10$^{\text{th}}$ grade performance in 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 participate in standardized national exams at the end of 12$^{\text{th}}$ grade. After students take these national exams, university 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 as university STEM degree programs all degree programs offered at Science university departments, as well as Engineering and Technology departments. Health sciences, such as Medicine and Biology are not considered STEM, nor Business and Economics.[17] The two outcomes variables are nested in the sense that only students who attended a STEM track in the 12$^{\text{th}}$ grade can apply to a STEM degree program.[18] Finally, we look at the

[12]We discuss the association between absolute STEM advantage on 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 achieve sufficient performance in 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 the performance in the first semester instead of the final exam performance in 10$^{\text{th}}$ grade.

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

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

[18]Students in the Classics track may apply to a STEM degree program at a penalty (in the form of reduction of their test scores) and only if they take national exams in the STEM courses. This scenario corresponds to a negligible

average performance in STEM subjects in grades 11 and 12, as an outcome.

3.1 Descriptive Statistics

Panel A of Table 1 shows the average performance by gender and subject. Females perform, on average, significantly higher than males in almost every subject. We plot those performance differences by gender in Figure 2. We show that indeed females outperform males much more in non-STEM than in STEM subjects.[19] Panel B in Table 1 shows that females' over-performance are even higher in non-STEM (=1.594) compared to STEM (=0.349). The class level differences for males and females are not statistically different from zero, indicating that the class randomization has been indeed successful. Combining these, females have a lower comparative advantage in STEM subjects compared to males (0.409 for females and 0.487 for males). Panel C shows that despite of females' over-performance 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 for a STEM university placement, conditional on attending a STEM track in previous grades. [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 (5th quintile). The bottom figure shows that in the top quintile of non-STEM performance, the proportion of females is much higher (75% are females, while only 25% are males). Table A1 shows summary statistics for STEM specialization by gender. The difference in comparative STEM advantage for individuals who specialize in STEM compared to 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 to specialize in STEM, ceteris paribus. In other words, we attempt to tease out the distinct role of comparative STEM advantage on future STEM specialization outcomes, while controlling for absolute STEM advantage.

share of the university applicants coming from the Classics track in high school. Our analysis on application for a STEM degree programs only considers candidates from a STEM high school track, for 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 males.

[21]We discuss Table A1 in Appendix.

Estimating the effect of comparative STEM advantage, on top of absolute STEM advantage, on future STEM specialization is challenging for several reasons. First, these absolute and comparative STEM advantages are correlated by construction, making 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, individuals, in the heuristic process of comparison, end up transforming complex assessments in manageable subjective tasks, 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 that students use for social comparison. Second, the economics literature document the distinct role of rank-ordered positions on 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, on top of 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 between student's absolute STEM advantage and 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 for each student her ordinal rank of absolute STEM advantage. 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 N. The student with the lowest absolute STEM advantage in the classroom is assigned an ordinal rank value of 1. In order a have 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 in her classroom. A student with an absolute STEM advantage of 1.4 is likely to have one of the highest comparative STEM advantage 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 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, therefore same absolute STEM advantages. These students may have different *rankings* in absolute STEM advantage (namely comparative STEM advantage), because they are assigned to classrooms with peers who have different performances 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 among 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. These two students are randomly assigned into 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 face two different comparative STEM advantages. 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:

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

where Y_{ijst} is the outcome variable for i student, in j classroom, in s school, and t cohort. It 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 of 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 non-linearly 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 that 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 students are indeed randomly assigned to classrooms and classroom numbers are not systematically associated with differences in student characteristics, average or the median classroom observable characteristics. In particular, we show that classrooms have similar average GPA (overall and by gender), proportion of females, average STEM and non-STEM performance (overall and by gender).

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

[27]As depicted in Figure 2 and in 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 (?).

STEM advantage. We 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), while using two different outcomes. For each outcome, we estimate six regressions which vary only in terms of the functional form of absolute STEM advantage that is used in the specification, while all other variables remain the same. The top panel shows the 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 remain almost unchanged in all non-linear 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 by 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 as sizable.

This suggests that students with a lower comparative STEM advantage may under-invest in STEM enrollment compared to 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 on future application for STEM degree program, only for females. 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 two years later. It is likely that between grade 10 and the end of grade 12 students interact with different peers in addition to their 10$^{\text{th}}$-grade classmates. Nevertheless, the effect of 10$^{\text{th}}$-grade comparative STEM advantage remains long lasting and significant.

We further examine the effect of comparative STEM advantage on students performance in STEM in 11$^{\text{th}}$ and 12$^{\text{th}}$ grade. A high comparative STEM advantage may potentially encourage study efforts in STEM. Table 4 displays the results. A higher comparative STEM advantage is associated with a significant increase in STEM performance in grade 11 (top panel) and grade 12 (bottom panel), only for females. In particular, a 10 percent 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 Non-linear Effects

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

STEM track choice (in our preferred specification, column 6 of Table 3) to find how much more likely would females who go into non-STEM 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 female and male. We multiply the effect of comparative STEM advantage for female by their average rank (0.19+0.409=0.077). We multiply the effect of comparative STEM advantage for male 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 the test score performance is out of 20, this results in an increase equivalent to about 2.5%.

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

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 students decision to enrol in a STEM track in the beginning of grade 11. Most of the effects appear small for boys 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 value 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 when moving from lower to higher rank positions, for females.

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 students decision to enrol in a STEM track in 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, the marginal effect of comparative STEM advantage by quintile of STEM performance in 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 we shown earlier, higher quintiles of non-STEM performance have a greater number of 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 the 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; the choice of STEM track in grade 11 (=0.156 compared to 0.161) and the application for a STEM university degree program (=0.087 compared to 0.102). This indicates that for females these two reference groups are similarly used when they make social comparisons. Among males, the effect of comparative STEM advantage with respect only to their male classmates is negative and small in magnitude, while in the main results (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 one's school-cohort instead of the classroom. The outcome variables that we focus on are a student's STEM track choice in grade 11 and application for STEM university degree program. For the estimates w use specification (4), while the comparative STEM advantage is computed based on one's school-cohort peers. While in the previous section we exploit variation in the dispersion of absolute STEM advantage across classrooms, controlling for classroom 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 to the main results (0.037 compared to 0.161 and 0.063 compared to 0.102) and statistically insignificant. In contrast, the estimates in the main results were statistically significant and different between 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 the peers they spend more instruction time with. Students may not be as aware of the performance of their school-cohort peers as they may be of the performance of the classmates. 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. Thus, there may be less variation in student characteristics between different 10^{th} grade cohorts of the same school than between classrooms of the same school-cohort.

5.1.5 Robustness Checks

So far we have assumed that comparative STEM advantage is orthogonal to the error term conditional on absolute STEM advantage, students 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 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 out 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 out from the school at the end of 10$^{\text{th}}$ grade, after they complete the grade.[35] We call these students *"attriters."* While for early leavers we do not have their performance at the end of grade 10, nor their future enrollment choices, for attriters we have their performance at the end of grade 10, but not their future enrollment choices. Males are more likely to leave grade 10 earlier or drop out from the sample 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% males and 13.3 % females are attriters.[36] One may worry that students with a lower comparative STEM advantage might be more likely to drop out during or after the end of grade 10. This 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 students attrition.

Then, we explore the association between comparative STEM advantage and students 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

[34]The compulsory schooling age in Greece is 15 years, the age most students graduate from 9th 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 a school drop out 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 part of the world. For example, in 2017-18 in Colorado, 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.

attrition is not associated with comparative STEM advantage. To further alleviate any concerns of 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 compared to 0.182, and 0.161 compared to 0.139, for the quadratic and non-linear 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 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 may worry that each student's final exam performance may be affect by the interaction 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, the earliest instance of performance measurement. Table 8 shows these estimates, which remain almost unchanged compared to the main ones. In particular, a 10% increase in comparative STEM advantage increases females' likelihood to enroll into a STEM track in 11^{th} grade by 1.7 percentage points, while the equivalent estimate for the main effect was equal to 1.6 percentage points. The results are robust to the usage 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 the first semester performance (=0.45) compared to 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 vast literature focuses on the under-enrollment of women in STEM disciplines, recent literature argue that gender differences in enrollment are concentrated especially in math-intensive science fields (Kahn and Ginther, 2017). Our definition of STEM degree programs so far includes only Science, Engineering and Technology departments, without including Economics, Business and Health Sciences.[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 Sciences are 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 where all three subjects are considered as STEM as a benchmark, while the last three columns shows the 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), 0.110 (Physics) compared to 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 the comparative non-STEM advantage has an effect on future study choices. We rank students within the classroom based on their absolute non-STEM advantage and we compute their comparative non-STEM advantage using (3). Table A9 reports the result for specification (4), when comparative non-STEM advantage is used. As expected, comparative non-STEM advantage has 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 male. The

[38] We follow the International Standard Classification of Education (ISCED) and define as STEM: 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 track can apply to Economics and Business and Health Sciences departments.

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

[41] This is the only subject in which there is not significant difference between male and female performances

magnitude of the estimates are similar as the ones reported in Table 3. Nevertheless, comparative non-STEM advantage has no effect on university application.

6 Potential Mechanisms

The previous sections have 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 of comparative STEM advantage for males and females. In this section we employ the terminology of 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, while the second is the non-monetary 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) non-monetary marginal utility, p, than the other occupation, it would require a lower (higher) advantage compared to one's peer(s) to justify specializing in the discipline related to the first occupation.

Males and females may have different monetary return 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 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. The two become:

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

where in both equations the LHS represent 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:

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

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 non-monetary return of choosing a specific specialization. Non-monetary return refers to preference or tastes. Males and females may face different non-monetary returns to specializing in STEM. First, STEM-related occupations tend to be more competitive than non-STEM-related occupations. Several paper state that females tend to shy away from the competition (Niederle and Vesterlund, 2007; Gneezy et al., 2003; Ors et al., 2013; Orrenius and Zavodny, 2015; Landaud et al., 2016). Secondly, many studies have explored societal and environmental influences in shaping female attitude towards STEM. [42] Part of the literature has also explored the role of teacher biases [43] ,parental investments, and beliefs [44] in shaping females preferences over STEM-related fields. Lastly, women are under-represented in STEM occupations in Greece (European Institute for Gender Equity, 2019). Dille (2018) and Yu (2020) claim that a greater exposure to positive female role models and mentors, especially in the technological sector, increases female's preference towards STEM-related occupations.

If females face lower non-monetary return 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 for them to choose a STEM specialization.

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

[43] Lavy and Sand (2015); Lavy and Megalokonomou (2019) document how 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 mother beliefs about their daughter's ability impacts performance and choice of taking additional courses in math.

7 Conclusion

In this paper, we show evidence that students might use two dimensions of comparison when they make schooling track, university degree and occupation specialization decisions. The first dimension is what we call *absolute advantage*, which refers to the within-individual relative academic strengths and weakness in STEM subjects compared to non-STEM ones. The second dimension is the *comparative advantage* and is about ones' relative standing of her absolute advantage within her peer group. 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 spans from 2001 to 2009 and is linked to students' university degree applications. We exploit the institutional setting in Greece in which students are practically randomly assigned to classrooms at the beginning of grade 10. We proxy one's comparative advantage in STEM subjects by using a student's 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 one'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 to a 4- or 5- year university degree in a STEM major 2 years later. Student study choices in grade 11 or later are more likely to reflect the decision of the student herself rather than the decision of her family.

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 lower comparative advantage. We find that increasing one's comparative advantage in STEM within her classroom by two positions increases her likelihood to enroll in a STEM track in grade 11 by 1.9% for females, but has much smaller or insignificant effect on males. We also find that one's comparative advantage in STEM in grade 10 has longer term implications. In particular, we find that an increase in one's 10^{th} grade comparative STEM advantage by 10%, increases her likelihood to apply to a STEM university degree program at the end of high school for around 1% for females, while males are less or not affected. Comparative STEM advantage has a significant effect on STEM performance in grade 11 and 12. Additionally, we find similar effects when the comparative advantage is computed within the same gender peers in the classroom, or within the school-cohort.

We conduct several robustness exercises to provide further credibility to the 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 drop out decisions. Second, we show that our results are robust of 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 on STEM study decision. Two mechanisms emerge from the model, that 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 that they would do so and they 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-individual and across-individuals is general and could be applied to other contexts. Any context where comparisons with competitors emerge along multiple dimensions, such as the labor or the mating market, could profit from our approach in quantifying the object of comparison. A benefit of using comparative advantage as a measure of relative strength is that it carries economic intuition. 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 Department	0.627	0.565	-0.062	0.000
Applied for an Economics and Business Department	0.272	0.228	-0.044	0.000
Applied for a Health Sciences Departments	0.119	0.321	0.203	0.000
Applied for a Humanities Department	0.363	0.626	0.262	0.000

Notes: Panel A reports the 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. The 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 the summary statistics for male and female students (columns 1 and 2, respectively), the gender difference between column (2) and (1) (column 3), and the 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	-0.483	0.316	-0.339	0.306	-0.454	0.294
	(0.129)	(0.153)	(0.022)	(0.357)	(0.324)	(0.310)	(0.259)	(0.337)	(0.327)
Class number=2	-0.230*	-0.291*	-0.029	-0.607*	0.377	-0.477	0.344	-0.627*	0.342
	(0.130)	(0.153)	(0.022)	(0.363)	(0.334)	(0.307)	(0.266)	(0.343)	(0.339)
Class number=3	-0.153	-0.206	-0.019	-0.429	0.276	-0.336	0.258	-0.448	0.270
	(0.129)	(0.153)	(0.021)	(0.355)	(0.316)	(0.306)	(0.252)	(0.334)	(0.321)
Class number=4	-0.122	-0.175	0.005	-0.064	-0.058	-0.117	0.013	-0.088	-0.076
	(0.128)	(0.154)	(0.022)	(0.359)	(0.318)	(0.305)	(0.245)	(0.336)	(0.326)
Class number=5	-0.028	-0.083	-0.006	-0.212	0.184	-0.154	0.280	-0.280	0.154
	(0.130)	(0.163)	(0.024)	(0.379)	(0.342)	(0.326)	(0.245)	(0.364)	(0.337)
Obs.	3,432	3,432	3,432	3,432	3,432	3,432	3,432	3,432	3,432
Mean of Y	14.42	14.32	0.55	8.19	6.23	5.93	4.72	7.75	5.60
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	2.36	1.90	2.04	1.75	2.41	2.10
P-value of F-model	0.06	0.12	0.06	0.04	0.10	0.07	0.12	0.04	0.07

Notes: The table shows results of the estimated effects of the classroom number on a variety of outcomes. The outcome variables are reported in the column. In particular, 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. The 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)	Non-linear (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 x 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 to STEM University Department					
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 x 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) , b) an indicator for whether a student applies for a STEM university degree two 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 non-linear specification, using binary indicators for each decile of the rank (column 6). Each regression controls for student absolute STEM advantage, but also STEM and non-STEM performance. Each regression includes 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)	Non-linear (6)
	STEM Performance in Grade 11					
Comparative STEM Advantage	-0.181	0.296**	0.302**	0.209	0.194	0.072
	(0.136)	(0.142)	(0.143)	(0.151)	(0.151)	(0.154)
Comparative STEM Advantage x Female	0.570***	0.571***	0.440***	0.441***	0.455***	0.463***
	(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	-0.041	0.214	0.263	0.157	0.144	0.064
	(0.198)	(0.210)	(0.215)	(0.226)	(0.226)	(0.226)
Comparative STEM Advantage x Female	0.839***	0.899***	0.798***	0.783***	0.794***	0.787***
	(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$^{\text{th}}$ grade (top panel), and 2) a student average performance in STEM subjects at the end of 12$^{\text{th}}$ 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 non-linear specification, using dummy variables for each decile of rank (column 6). Each regression controls for a student absolute STEM advantage, STEM and non-STEM performance. Each regression includes 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)	Non-linear (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 x 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 to STEM University Department			
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 x 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 non-linear specification which uses dummy variables for each decile of rank (column 6). Each regression controls for student's absolute STEM advantage, STEM and non-STEM performance. Each regression includes 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)	Non-linear (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 x 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 to STEM University Department					
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 x 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 non-linear specification, using dummy variables for each decile of rank (column 6). Each regression controls for student absolute STEM performance, non-STEM performance, and absolute STEM advantage. Each regression includes 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 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

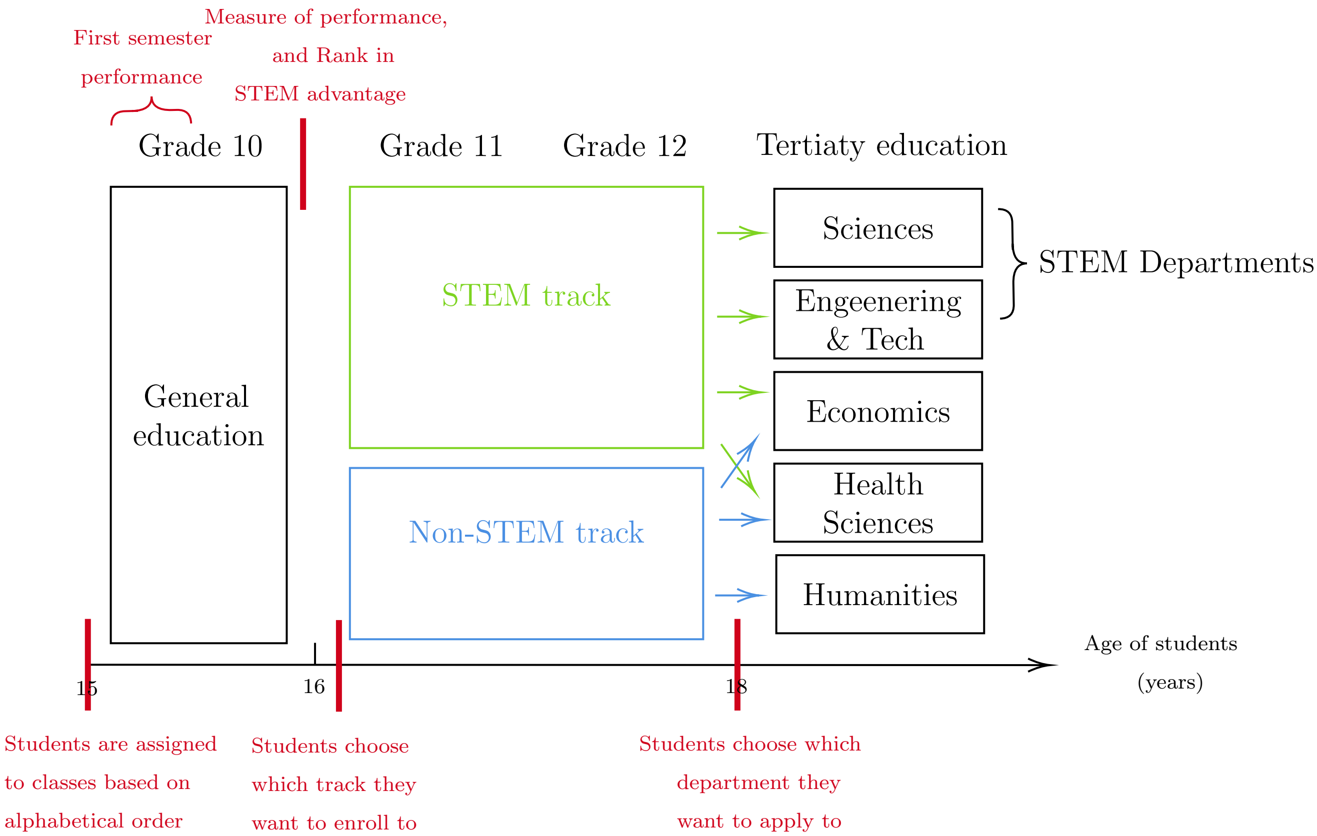
Notes: This table reports results of the estimated effects of the comparative STEM advantage on grade attrition in grade 11. The estimates are derived using specification (4), while the outcome variable is an indicator that becomes equal to one if a student drops out from the sample. The model controls for a second order polynomial for absolute advantage in STEM, student's absolute STEM advantage, STEM and non-STEM performance. The model also includes 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)	Non-linear (6)
			STEM Track in Grade 11			
Comparative STEM Advantage	0.088***	0.017	0.014	-0.011	-0.008	-0.006
	(0.015)	(0.016)	(0.017)	(0.018)	(0.018)	(0.019)
Comparative STEM Advantage x Female	0.188***	0.209***	0.168***	0.174***	0.171***	0.168***
	(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 to STEM University Department			
Comparative STEM Advantage	-0.016	0.010	-0.008	0.001	0.001	0.005
	(0.020)	(0.023)	(0.023)	(0.025)	(0.025)	(0.026)
Comparative STEM Advantage x Female	0.064***	0.056**	0.051**	0.046*	0.046*	0.045*
	(0.024)	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)
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

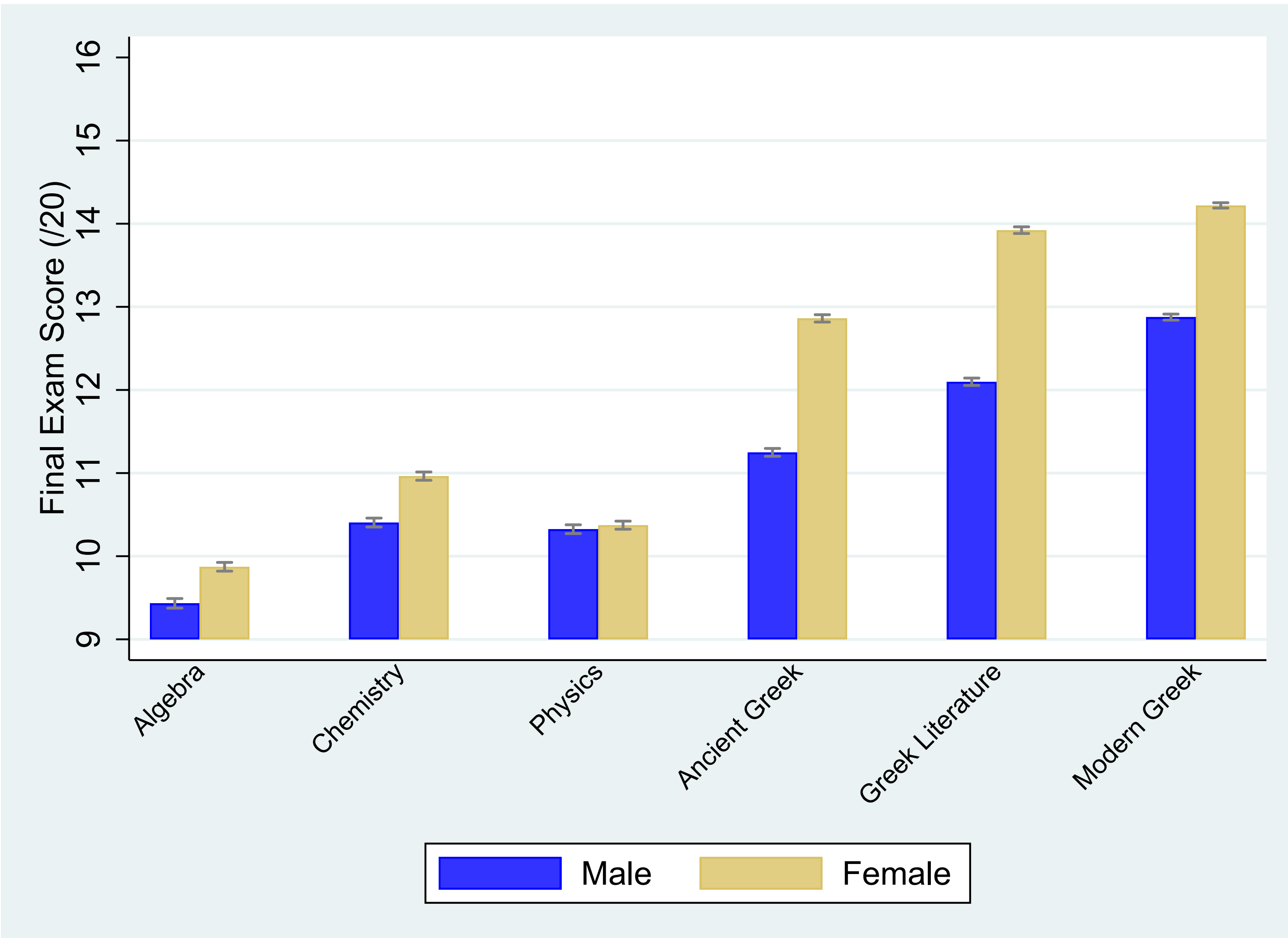
Notes: This table reports results of the estimated effects of comparative advantage using the main specification (4), while now we compute comparative advantage based on a student's midterm performance in semester A, rather than her final exam score (Table 3). Each regression controls for a student absolute STEM advantage, STEM and non-STEM performance. Each regression includes 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**



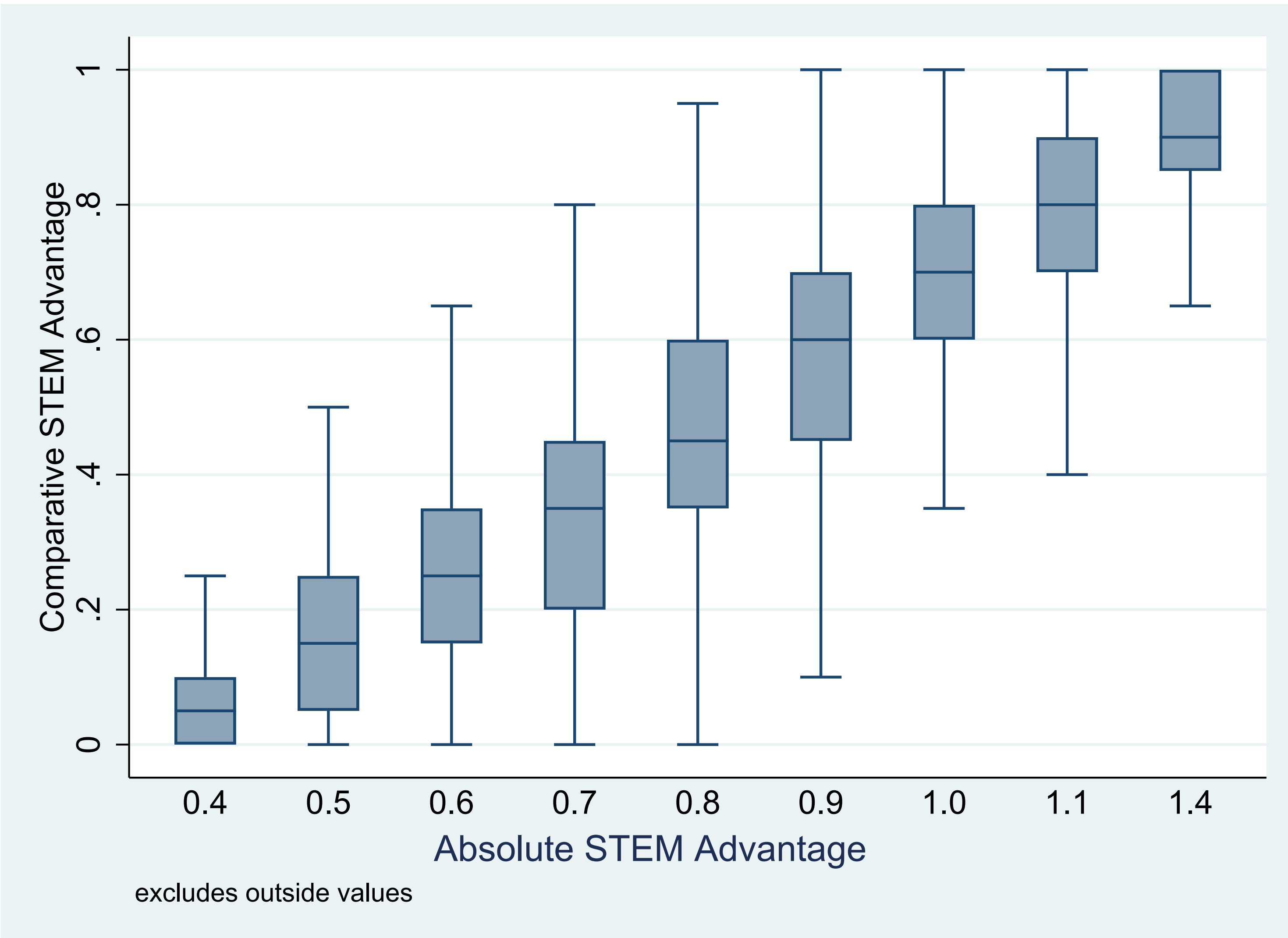
Notes: This figure displays the timeline of student decisions from senior high school to university. At the beginning of grade 10, students are assigned to the high school serving the zone of their residential address. Students start high school at the age of 15. The compulsory school age in Greece is 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 participate in 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**



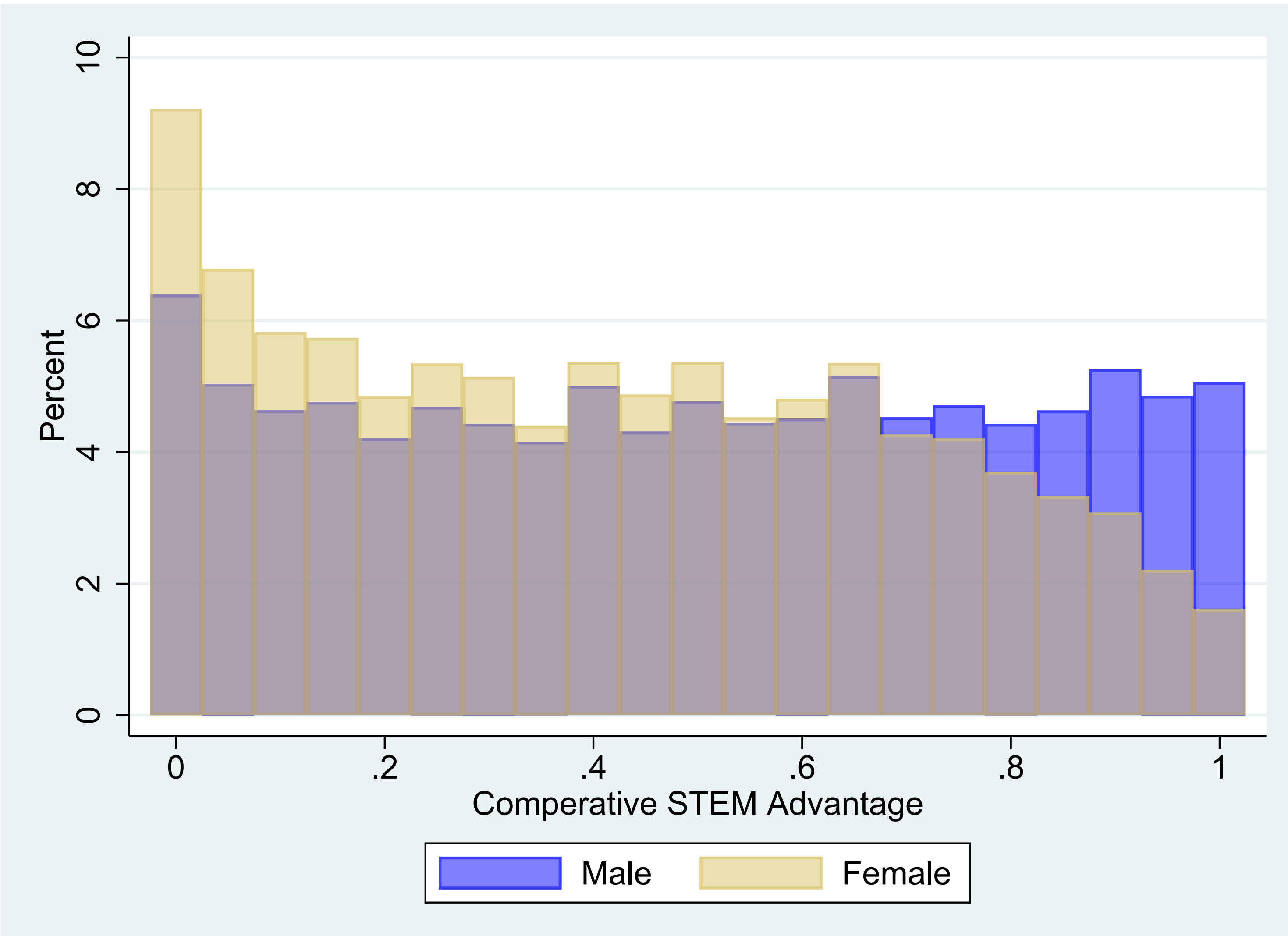
Notes: This graph displays the performance (out of 20) in six subjects, for males and females separately. Final exam scores are used to measure student performance. Females perform significantly better in almost every subject (except for Physics, where the difference is not statistically different from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

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

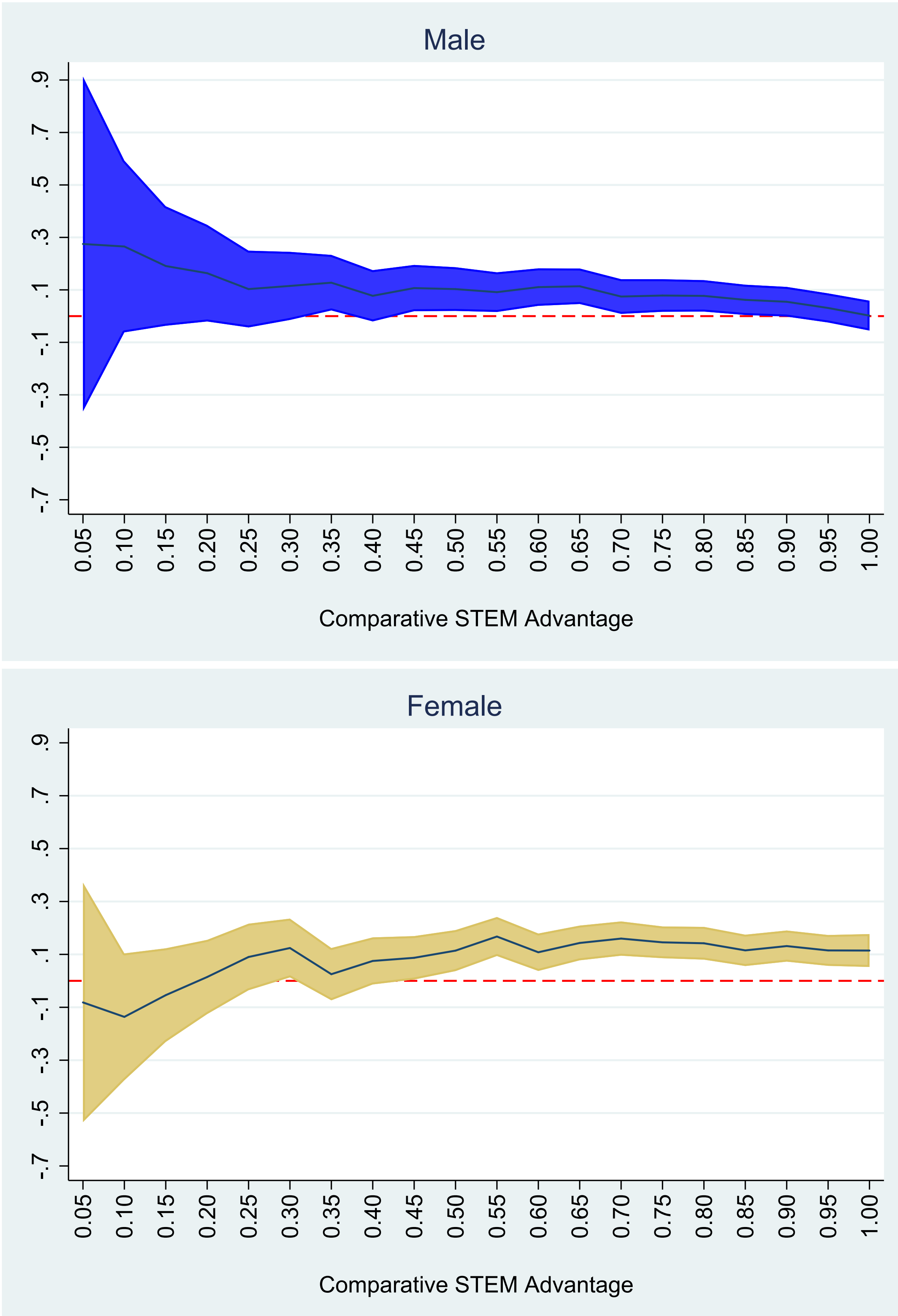


Notes: This figure shows the percentage of females and males in each percentile rank in STEM advantage. Interestingly, females are much more likely to have lower percentile rank in STEM advantage than males, and much less likely to have high percentile rank in STEM advantage.

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 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: **Non-linear 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 are considered, 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 into a non-STEM (columns 1 and 6) and STEM track in 11^{th} grade (columns 2 and 7), separately. As shown in columns 1 and 2, males who enroll into a STEM track in 11^{th} grade have a higher STEM performance but slightly lower non-STEM performance in 10^{th} grade than males who go into non-STEM in 11^{th} grade. The corresponding differences and p-values are shown in columns (3) and (4), respectively. Females who enroll into a STEM track in grade 11 (column 7) have a higher performance in both types of subjects compared to females who go into a non-STEM track (column 6). The corresponding differences in column (8) and 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) and (6) as well as (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^{th} grade performance in both types of subjects compared to those who do not apply to a non-STEM degree program. The 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 students own performance in STEM and non-STEM subjects in grade 10, classroom average performance in STEM and non-STEM 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 difference between non-STEM and STEM enrollment.

The Effect of Absolute STEM Advantage

In this section, we examine empirically the following hypothesis: the fewer contenders there are that outperform an individual in terms of competence in STEM relative to non-STEM, the more likely that individual is to specialize in STEM, while controlling for own and his/her contenders' competence in STEM relative to non-STEM.

An individual's competence in STEM relative to his/her competence in non-STEM can be proxied using definition (2). A similar definition can be used to proxy one'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 to the likelihood of apply 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 Department	
	(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 explores the patterns of track choice in grade 11 and university departments application. Importantly, this table has no intent to identify causal inference, but rather questioning whether the gender gap in STEM enrollment can be explained by gender difference in students performance. The table reports the results of a specification in which the track enrollment and university application decisions of student's i, in school j, cohort t are regressed on his/her 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 Department	
	(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 departments application. Importantly, this table has no intent to identify causal inference, but rather questioning whether the gender gap in STEM specialization can be explained by gender difference in students performance. The table reports the results of a specification in which the track enrollment and university application decisions of student's i, in classroom j, in school s, in cohort t are regressed on his/her 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 Sample Selection

In order to deal with the possible bias induce by sample selection, we employ an Inverse-probability-weighted estimators 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 students 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. The 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 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 more weight to students who have similar characteristics than ones subsequently transfer out than to students with characteristics that make them more likely to remain in the same school. Table A6 shows the main result for our model when attrition is not controlled for, and when it is controlled. The results are remain similar.

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 students attrition ratte (in columns 1 and 2 respectively). Column 3 reports the gender differences in early leavers and students 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 attritions. 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 as *attriters* students who leave the sample at the end of 10^{th} grade and after they complete garde 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	Non Linear	Quadratic	Non Linear
	(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 x 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 x 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 the OLS estimates for model (4), without correcting for attrition (columns 1 and 2), and using IPWs to account for attrition (columns 3 and 4). In each regression, the dependent variable is a dummy for whether the student apply to a STEM track at the end of grade 10. The first specification includes a quadratic term for STEM advantage; while the second specification includes 10 dummies for different level of absolute STEM advantage. 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 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)	Non-linear (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 x 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 x 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 x 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 the 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 department are included in the definition of STEM. Panel C shows the results when Health Sciences departments are included in the STEM definition. In each panel, we estimate several specifications for different degrees of polynomials for STEM advantage (columns 1-5); as well as a flexible specification with dummy variables for each decile of absolute STEM advantage (column 6). The last row in each panel shows the estimated coefficient of the interaction of comparative STEM advantage with the female indicator.Each regression controls for student STEM performance, non-STEM performance, absolute STEM advantage, and 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 (STEM=Algebra, Chemistry, Physics)	0.030			
	(0.021)			
Comparative STEM Advantage (STEM=Algebra, Chemistry, Physics) × 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 the OLS estimates for model (4), using different definitions of STEM advantage: in column (1) STEM is defined as 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 are always defined as average performance in Modern Greek, Greek Literature, and Ancient Greek. Each column controls for student STEM performance, non-STEM performance, absolute STEM advantage, and classroom FE. We use a flexible specification with dummy variables for each decile of absolute STEM advantage. The dependent variable is an indicator for whether the student enrolled in a STEM track in grade 11. 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 Department	
	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 female. 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. 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 10th Grade

In this section, we employ performance in the first semester of 10th grade to compute students' absolute and comparative STEM advantage. Students are allocated to classrooms at the beginning of grade 10. Therefore, student's final exam scores at the end of the year, which determines 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 decide to use performance at the end of first semester in grade 10, as robustness check. Table A10 shows the summary statistics when performance in semester 1 of 10th grade are used. Figure A7 shows the performance in first semester of 10th grade for males and females in Algebra, Physics, Chemistry, Modern Greek, Greek Literature, and Ancient Greek. Table 8 report the estimates of our main model using these performance. The results remain robust.

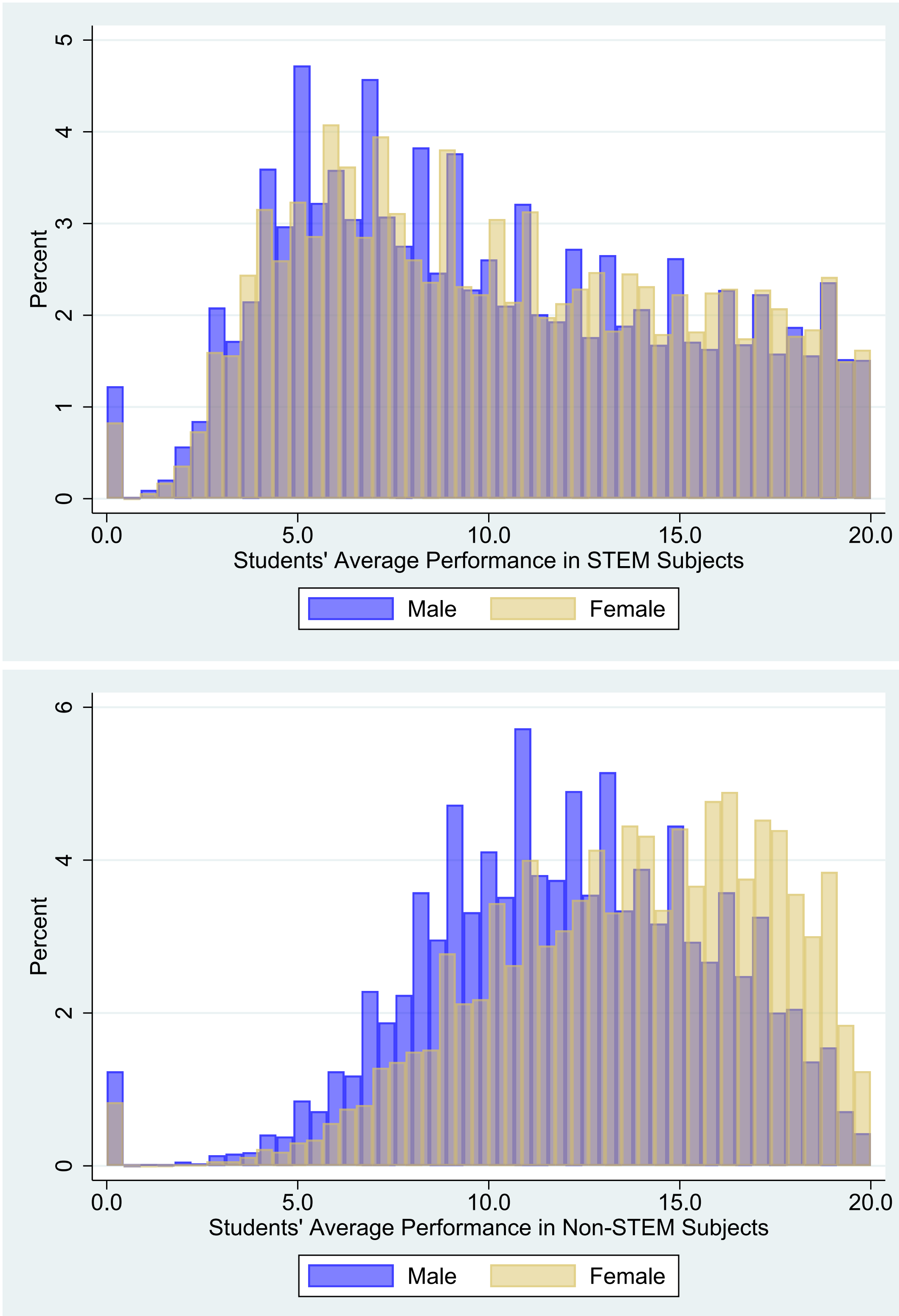
Table A10: **Descriptive Statistics: using Performance in First Semester 10th Grade**

	Male (1)	Female (2)	Difference (3)	*p-value* (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); the gender differences for the variable we construct and we use for our analysis (Panel B). The forth column reports the p-values for the t-test on the gender difference on each variables.

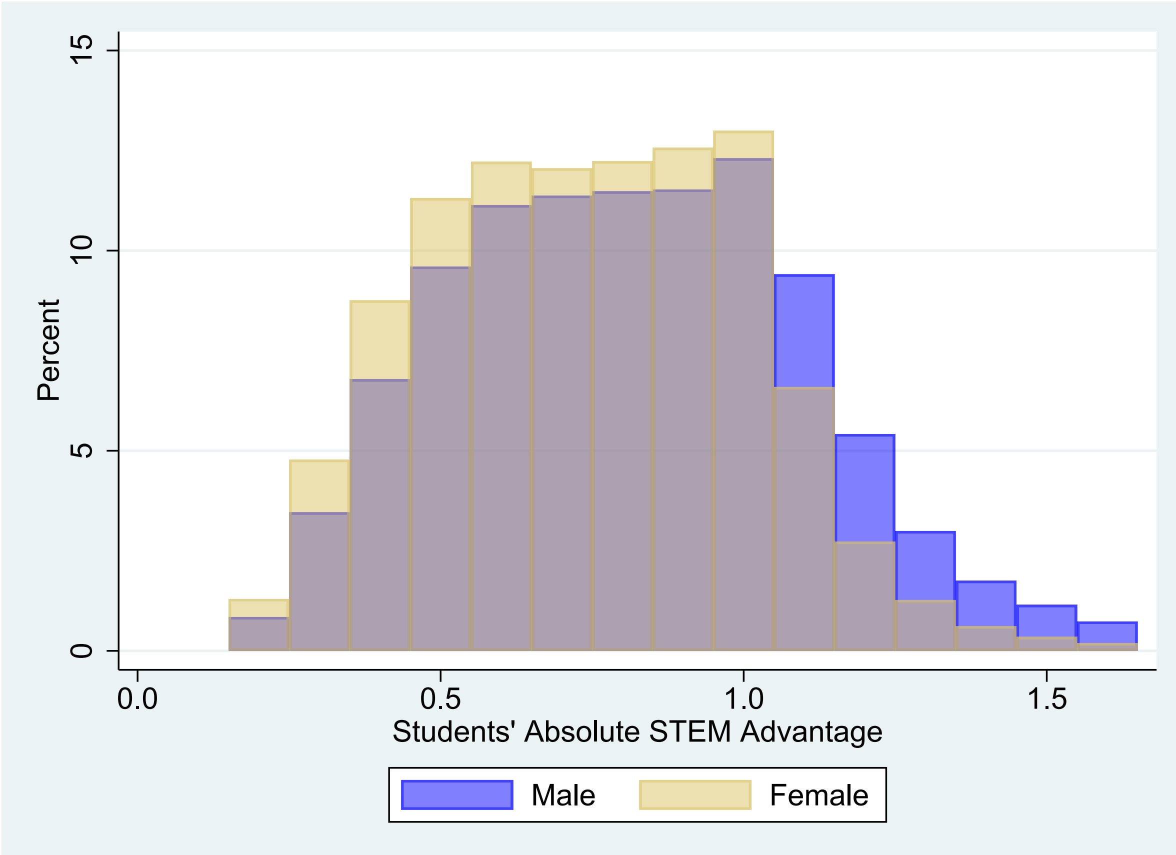
Appendix Figures

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



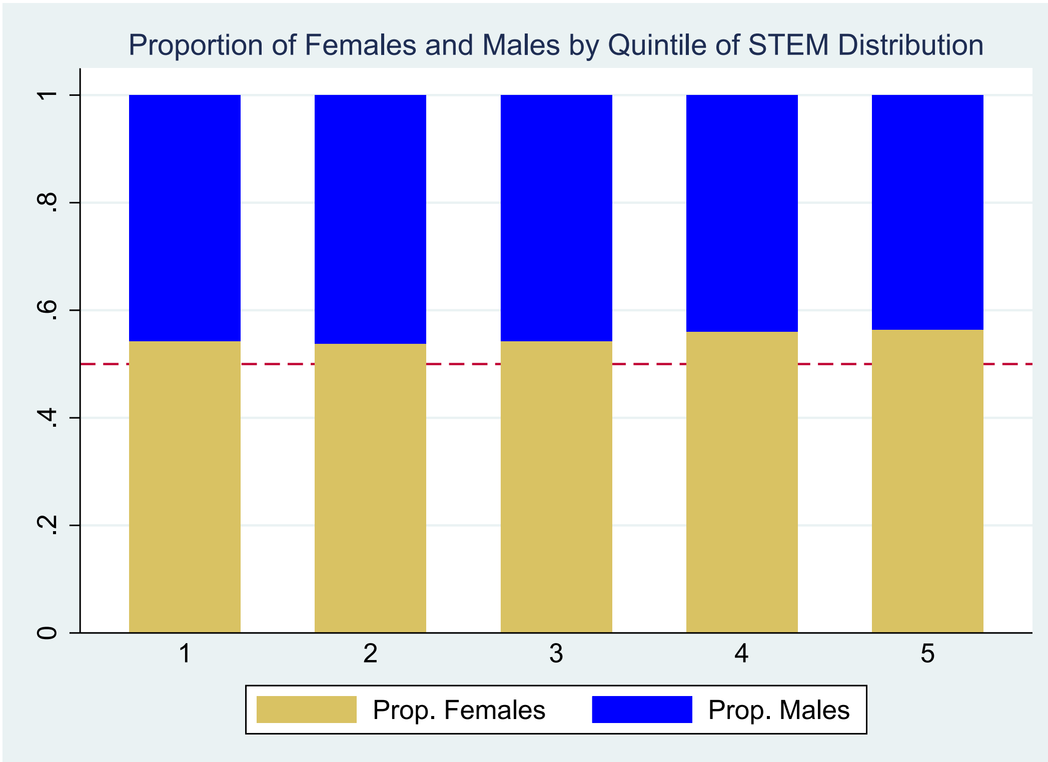
Notes: These two graphs plot the distributions of performance at the end of 10th grade for STEM subjects (Maths, Physics, and Chemistry) in the first graph, and non-STEM subjects (Modern Greek, Ancient Greek, and Greek Literature) in the second graph.

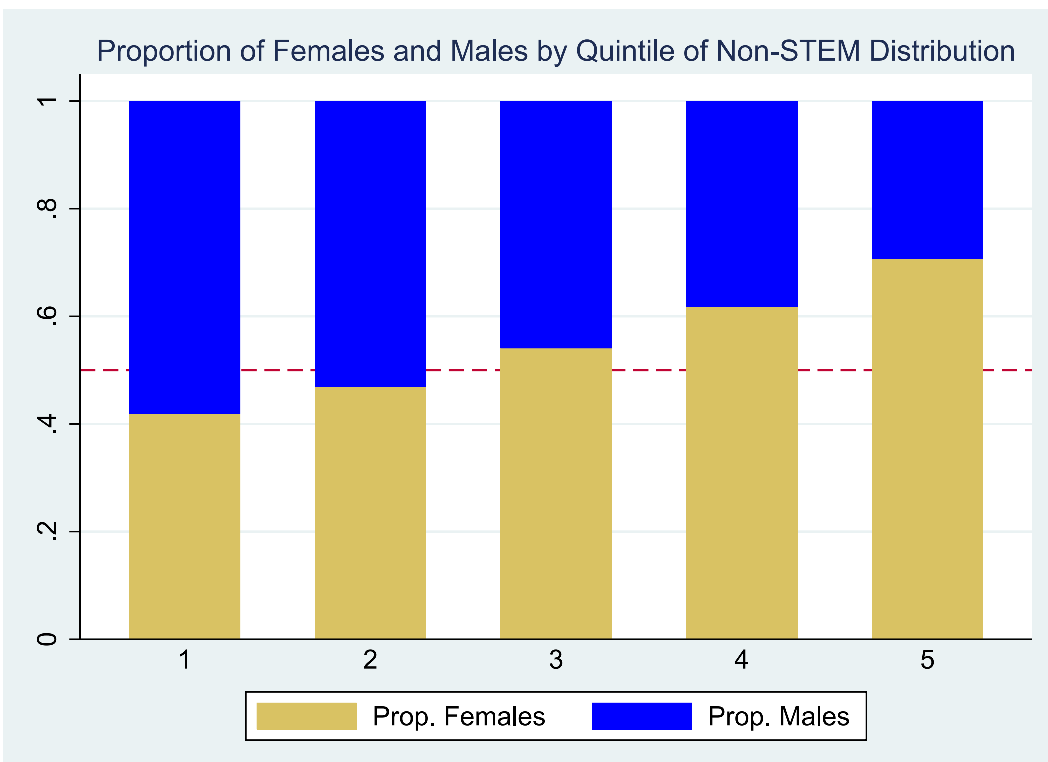
Figure A2: **Distribution of Absolute STEM Advantage at the End of 10th Grade**



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

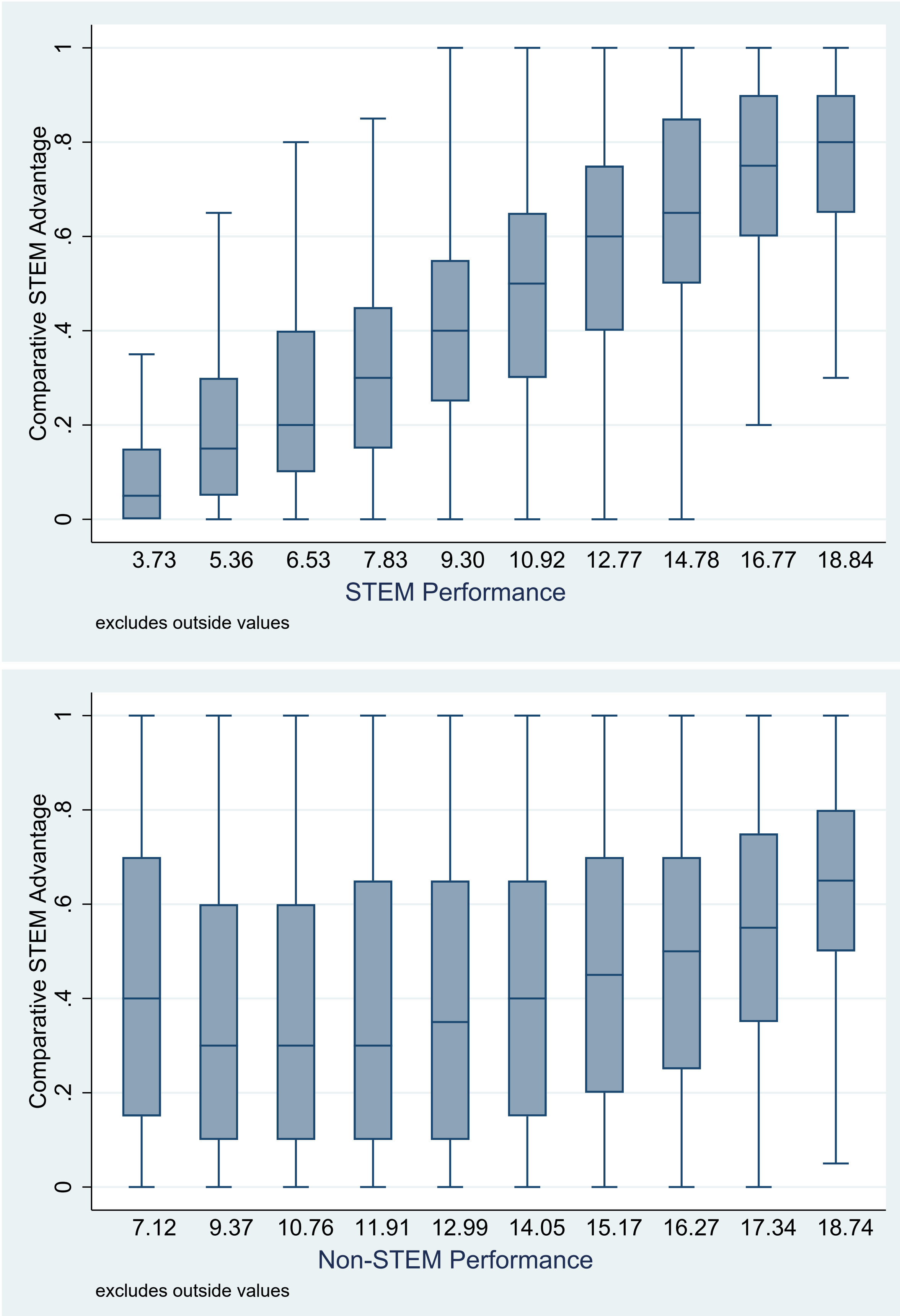
Figure A3: **Proportion of Males and Females by Quintile of STEM/Non-STEM Performance Distribution**





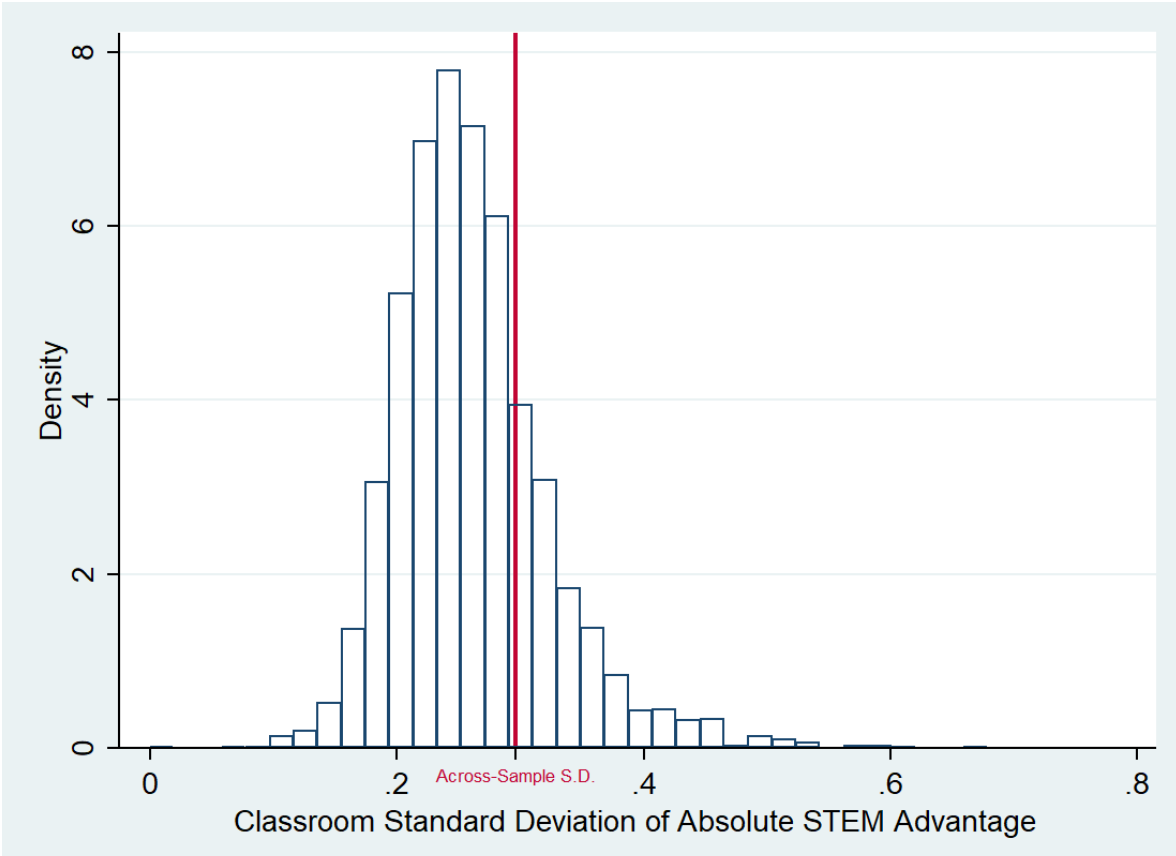
Notes: These two figures show the proportion of students by quintiles of the STEM and non-STEM performance distribution at the end of grade 10. STEM ability is computed as average GPA in Algebra, Physics, and Chemistry. Non-STEM performance is computed as average GPA in Modern Greek, Greek Literature,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



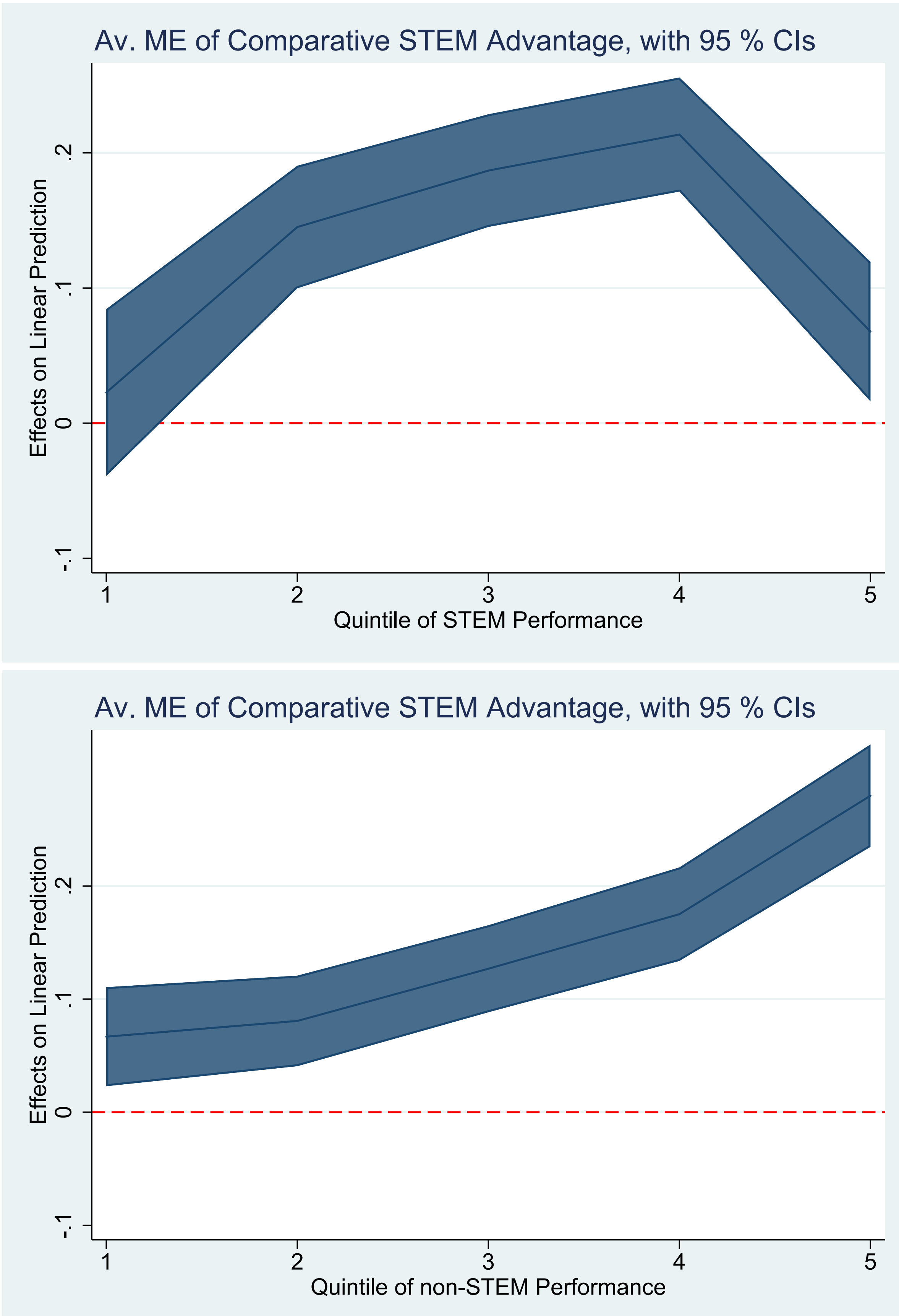
Notes: These two box plots show the variation in rank in STEM advantage by decile of the STEM and non-STEM performance at the end of grade 10.

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



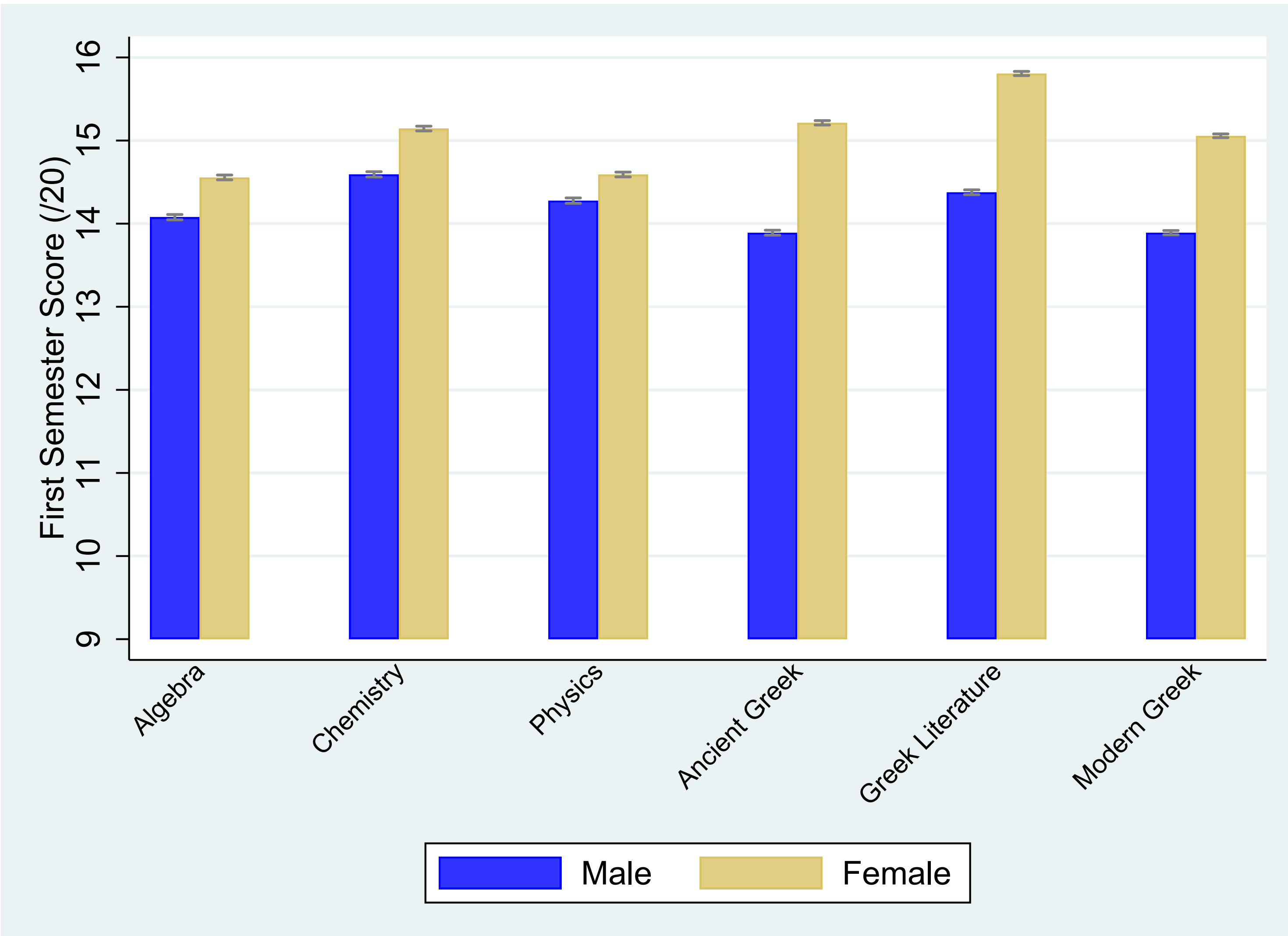
Notes: The histogram of within-classroom standard deviation of absolute STEM advantage reveals substantial variation in the dispersion of absolute STEM advantage in the classroom. The vertical line corresponds to the standard deviation of absolute STEM advantage across all students.

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).