To inspire and to inform: The role of role models*

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Abstract

We study the effects of a randomized role models intervention in which female engineering students gave presentations at high schools about their experiences in the major. Among girls, we find an increased preference for engineering majors for those in the top math ability quartile; with stronger effects for those who reside geographically close to the role models' university. Inspired by role models, high math ability girls had increased self-confidence for succeeding in engineering majors. We also find smaller positive effects for "low math ability" boys, likely as a result of the talks emphasizing skills besides math for success in engineering.

Keywords: STEM gender gap, role models, career choices, stereotypes, RCTs.

JEL Classification codes: C93, I23, I24, J16.

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1 Introduction

Despite significant progress in women's access to college education in recent decades, there is still a gender enrollment gap in Science, Technology, Engineering, and Mathematics (STEM) majors. Within STEM disciplines, women's participation in engineering, one of the primary STEM fields, remains significantly below that of males in both developing and developed countries. For instance, while in the 2017-18 academic year 57% of bachelor's degrees were conferred to women in the United States; just 13% of bachelor's degrees in engineering were awarded to females.[1] A recent report by UNESCO (2017) shows that in Latin American countries, such as Colombia and Mexico, the female participation rate in engineering majors is lower than 35%, and that worldwide, only 8% of the female student population choose engineering related fields of study. The gender participation gap in engineering has profound consequences for women in particular and society in general. It contributes to the under-representation of females at the top of the income distribution,[2] has negative effects for the development of new ideas, science, technology and firms productivity, and critical repercussions on economic growth via the misallocation of talent.[3]

Understanding the causes of low female participation in STEM fields continues to be an important research and policy question that has been studied by professionals in various fields. Several factors have been proposed as determinants of the observed gender STEM gap, such as differences in biological characteristics (brain structure), peer effects, individual preferences and beliefs, external validation, self-perception of ability, and social norms. With respect to differences in brain structure, there is a broad consensus that it does not account for the observed differences in math performance across genders, and that it is not related to the low enrollment of women in STEM careers [Ellison & Swanson (2010), Nollenberger et al. (2016), UNESCO (2017)]. Alternatively, other researchers have examined non-cognitive abilities (i.e. self-efficacy, self-perception) as potential drivers of the lack of women in STEM [Correll

[1] Digest of Education Statistics, National Center for Education Statistics (NCES). See: https://nces.ed.gov/programs/digest/d19/.

[2] See for instance, Blau & Kahn (2017).

[3] Detailed discussions can be found in Bear & Woolley (2011), and Hsieh et al. (2019).

(2001), Eble & Hu (2020), Kahn & Ginther (2017)]. Within STEM fields, the evidence strongly suggests that engineering has a low proportion of females mainly due to women's perception that engineering is a career not suitable for them [Emerson et al. (2012)]. Moreover, these stereotypes are transmitted to girls from a young age. Girls consider engineering as a "masculine" domain and believe that women cannot succeed there [Reuben et al. (2017), Eble & Hu (2022)], as they lack the necessary skills as well as due to the discrimination faced by women from STEM fields in the labor market [Bayer & Rouse (2016)]. Additionally, some authors point out the competitive nature of STEM fields as a reason for the low participation of women in Science and Engineering careers [Gneezy et al. (2003), Niederle & Vesterlund (2007), Niederle & Vesterlund (2010), Buser et al. (2014), Flory et al. (2014)].

This paper addresses an important, yet under-studied factor that can play a key role in explaining the gender gap in STEM careers: the lack of appropriate female role models. Growing up, most of us have had that one person(s) we have looked up to, were inspired by, and hoped to emulate. However, several barriers restrict young girls from having female role models in STEM, such as their relative scarcity in many contexts, as well as the absence of initiatives that bring the experience of the few existing ones to young girls. It is therefore difficult for high school girls to come into direct contact with women who have majored in or are majoring in STEM fields, such as engineering. Working with an elite private university in Peru, Universidad de Piura (UDEP),[4] we designed an intervention that aims to alleviate this problem by bringing those relatively scarce role models close to high school girls.

Our field experiment implemented classroom talks in which female senior college students or very recent graduates in engineering fields from UDEP, with first-hand experience and knowledge on the skills, aptitude and motivation needed to major in engineering, communicated and interacted with senior-year high school students in Northern Peru. We exploit this experimental setting to test whether exposure to female senior students/recent graduates in engineering acting as role models can change

[4]UDEP is a private university in Peru. It ranks among the top ten universities in Peru according to the QS Latin American University Rankings 2020.

high school girls' engineering perceptions, self-confidence and ultimately increase the proportion of girls preferring engineering majors at college.[5] Our total sample roughly contains 5,000 students in 11th grade, which is the final year of secondary education in Peru, and a period when most high school students start looking for higher education opportunities.

The task of the role models was to deliver a 20-minute motivational presentation in treatment schools and to answer questions thereafter. The role models provided information to students in selected schools based on a set of slides. Overall, the main message transmitted to students can be summarized in the following lines:

"You do not need to be mathematical genius to become a successful engineer", "Boys and girls have the same intellectual capacity even though their brains are physically different", "women are very creative and they can contribute to new ideas","To study Engineering creativity, ingenuity, effort, and desire to change the world are also very important".

Being in a treated school increases the probability that a female student in the upper quartile of the baseline math score distribution and in schools located close to UDEP (Piura region), would plan to enroll in any type of engineering by 14.1 percentage points. This corresponds to a more than 77% increase in preferences for engineering in treatment schools compared to the control ones. To our surprise, in some specifications we find weak evidence suggesting that boys in the two lowest math ability quartiles increase their preferences for engineering majors by 6 to 7 percentage points.

To shed light on the possible mechanisms underlying these results, we find that the treatment significantly increased high math ability girls' self-confidence in their aptitude and skills to perform well in engineering majors. Moreover, the treatment increased their interest in the engineering majors of the role models. This points to role models as a source of inspiration. In the case of boys, the mechanisms are less clear; but the evidence suggests that they are related to the specific information provided in the talks, which stressed that skills other than math ability are also relevant in engineering

[5]We center our analysis on preferences for engineering self-reported by the students in the follow-up survey rather than actual enrollment since at the time of the survey students were still applying to universities. Only 25% of students who planned to study engineering had already registered at a university.

majors. It is also important to highlight that our results related to the potential mechanisms are also stronger among students that reside within UDEP geographical area of influence. Taken together, all these suggest that not everyone can be an effective role model in any type of context.

Early studies that assess the effectiveness of role models on students' academic performance, students' enrollment, drop-out decisions and occupational choices within STEM majors mainly focused on the role of teachers or instructors.[6] However, many of these studies suffer from identification issues related to the unobserved preferences of instructors towards same gender students [Zeltzer (2020)], as well as the self-selection of students choosing to attend classes with instructors who they like the most, or have less strict grading policies. Because of these constraints, causality cannot be clearly established. Our paper isolates the role model channel through random, exogenous, variation in role model exposure, while focusing on female role models who are not instructors. Other studies have also analyzed the effects of non-teaching role model interventions in the field [Beaman et al. (2012), Del Carpio & Guadalupe (2018), Ashraf et al. (2020), Porter & Serra (2020), Breda et al. (2020), Brooks et al. (2018), Lafortune et al. (2018)].

Most closely related to our paper is a recent study by Porter & Serra (2020). The authors assess the effect of simultaneous exposure to two female role models, who are professional economists, on college freshman students' decisions to major in Economics. The authors show that a brief exposure to a female role model increases students' academic performance and influences their choice of major. Our study also investigates the effect of a brief role model exposure, but departs from Porter & Serra (2020) in several ways. Most importantly, our paper's goal is to understand the engineering related career choices of female high school students in a developing country where strong gender stereotypes are prevalent in engineering fields. This is significantly different from studying career choices of students already enrolled in college in a developed country and in non-engineering majors. Another experimental study also related to ours

[6] Although this is not an exhaustive list, a wide range of issues relevant to this aspect can be found in the papers by Neumark & Gardecki (1998), Bettinger & Long (2005), Dee (2007), Hoffmann & Philip (2009), Carrell et al. (2010), Bottia et al. (2015), Eble & Hu (2020), Lim & Meer (2017), Kofoed & McGovney (2019), and Lim & Meer (2019).

is the one by Breda et al. (2020). In this study, middle-aged female role models (i.e. scientists and PhD students) were able to influence French high school students' perception towards STEM fields. The classroom interventions in this study lasted one hour and consisted of a combination of videos and slides shown during the role model visits. A critical difference of our high school study context relative to that in Breda et al. (2020), is that in Peru, as well as in many other developing countries, there is no science track that separates students as a function of their preferences or skills for science majors. Also importantly, the role models in our intervention are senior college students or very recent graduates in engineering, and therefore younger and closer in age to the target group than the role models in Breda et al. (2020) and Porter & Serra (2020). Therefore, we expect our role models not only to motivate high school students, but also high school students to feel more connected to them.

Our paper relates to three strands of the literature. First, it adds to the extensive body of research on the causes of the STEM gender gap, particularly in engineering. There is a broad consensus that gender differences in brain structure are unlikely to explain this gap [Hyde (2005), Spelke (2005)]. In contrast, the literature points out to stereotypes and social norms as critical at influencing career choices and contributing to gender segregation across college majors. Our study shows that brief interactions with external (non-teaching) female students or recent graduates in engineering disciplines can influence girls' perceptions, self-confidence and ultimately their career preferences. Second, the paper contributes to studies in social psychology that look at the effect of gender stereotypes on women's under-representation in science. Several studies in social psychology have analyzed mentoring programs and non-teaching role model interventions like Macphee et al. (2013), but have not been successful at tracking the causal effects on career choices and isolating the related mechanisms. Our paper fills this gap as well. Third, different from a number of studies that investigate role model effects in non-face-to-face contexts (TV shows, inspirational videos shown to randomly selected individuals),[7] ours relies on direct communication between role models and the target population.

[7]See for instance, Riley (2017), Kearney & Levine (2019).

The remainder of the paper is organized as follows. Section 2 describes the Peruvian educational system, the status of females participation in STEM fields and the context and setting of our experiment. Section 3 presents the data and empirical strategy. Section 4 presents the intervention results and discusses potential mechanisms. Robustness checks are presented in section 5, while additional heterogeneous effects are discussed in section 6. Section 7 concludes and discusses policy implications of these findings.

2 The Experimental setting

2.1 Peruvian Education System

The school system in Peru consists of six years of elementary education followed by five years of secondary education. School attendance in the country is compulsory from ages 5 to 16. Approximately 2.5 million students are enrolled at the high school level,[8] and 15,000 high schools are active across the 25 country regions.[9] At the high school level classes are usually administered by different instructors depending on the subject, and the school year runs from March to December.[10] While the government runs a public school system, for-profit and not-for-profit private schools also exist. The curriculum, which is defined by the Ministry of Education and must be followed by all schools in the country, does not distinguish between students who aim to pursue STEM and non-STEM college majors at any level of basic or high school education. Furthermore, Peru does not have a centralized university admission system and each university is responsible for its own admission process. In public universities, admission basically depends on a general examination test set by each university. In some

[8] 76% of students are enrolled in a public school, and 90% of students are registered in schools located in urban areas. Source: 2017 Census of Schools, Ministry of Education (MINEDU), http://escale.minedu.gob.pe/resultado_censos.

[9] The Peruvian territory is divided into three administrative units: i) 25 regions, ii) 196 provinces, and 1,874 districts (municipalities). There are in total 8 provinces and 65 districts within the Piura region.

[10] Subjects that form part of the common National Curriculum are Mathematics, Communication, Foreign Language, Art, History, Geography, Economics, Civic, Social Skills, Physical Education, Religious Education, Science, Technology, and Environmental Studies.

private universities, other admission mechanisms are also present.[11]

The schools in our intervention sample are located in 6 out of the 25 regions in Peru, all of them in the northern part of the country, as it can be observed in Figure A5 in the Appendix. Roughly 60% of the schools (64 schools) are in the Piura Region, where UDEP's main campus is located. Of the remaining schools in our sample, 11 schools are located in La Libertad, 12 in Cajamarca, 3 in Ancash, 12 in Lambayeque and 7 in Tumbes.

While STEM careers cover various disciplines, in Peru engineering is by far the preferred STEM program among high school graduates. During the period 2016-2017, 93% of the roughly 417,000 students who applied for admission into a STEM field did so in engineering.[12] As in other countries around the world and in the Latin American region, in Peru, females are underrepresented in STEM fields in general and in engineering majors in particular. In this Andean country, during the period 2016-2017 only 30% (1 out 3) of those applying for admission into a STEM field[13] were women.[14] Moreover, while roughly just one in five (19%) female college applicants across the country selected engineering majors during this period; close to one in two (46%) male applicants chose an engineering program.

2.2 Universidad de Piura

UDEP is a not-for-profit private university located on the city of Piura, in the northern coast of Peru. According to recent national rankings, UDEP is one of the top 10 private universities in Peru, and the top ranked university in the northern region of the country. Historically, UDEP students come predominantly from the Piura region; however UDEP has also consistently attracted students from the neighbouring regions of Lambayeque (to the south) and Tumbes (to the north). Students from these three regions constitute about 95% of the UDEP Piura campus student population.

[11] For example, some private colleges offer direct admission to students in the upper third of their class GPA distribution.

[12] Administrative records of the Peruvian National Superintendence of Higher Education (SUNEDU): https://www.sunedu.gob.pe/sibe/.

[13] STEM fields include Biology, Mathematics, Statistics, Engineering, Physics, and Chemistry. Medical undergraduate studies, such as nursing and medicine, are not considered STEM in the Peruvian national statistics. In medical undergraduate studies, women are over-represented (70% are women).

[14] Administrative records of the Peruvian National Superintendence of Higher Education (SUNEDU): https://www.sunedu.gob.pe/sibe/.

In this sense, UDEP's prestige and reputation as a regional university is mainly concentrated in Piura region and the neighbouring regions of Tumbes and Lambayeque, which we refer to as UDEP's catchment area. Established in 1969, the UDEP Piura campus has approximately 6,500 undergraduate students across 15 academic programs. Within the category of STEM majors, the Piura campus only offers programs in Engineering.[15] In general, high school students application patterns at UDEP resemble those observed at the country level. According to the university administrative records, only 20% of all female applicants at UDEP selected engineering majors during the period 2016-2017. Moreover, 65% of engineering applicants were male, while just 35% were female.

2.3 The field experiment

Experimental design and randomization. The experiment started in early 2018 and was carried out in 18 cities.[16] These cities have a total of 225,000 high school students spread across 880 schools with women making up nearly half the student population.[17] Our team had access to a list of 150 schools within this area which have been frequently visited by UDEP admission officials in the last five years to promote the university and encourage applications. We finally chose 109 schools that make up our experimental sample,[18] which overall includes 5,378 students in the 11th grade.[19]

The randomization was stratified at the city level. Half of the schools in each city were assigned to the treatment group with the other half serving as controls. In total 51 and 58 schools were randomly assigned

[15] UDEP offers Engineering fields such as Civil Engineering, Industrial and System Engineering, and Mechanical and Electrical Engineering.

[16] The cities were Cajamarca (Cajamarca), Catacaos (Piura), Chiclayo (Lambayeque), Chimbote (Áncash), Chota (Cajamarca), Chulucanas (Piura), Cutervo (Cajamarca), La Union (Piura), Pacasmayo (La Libertad), Paita (Piura), Piura (Piura), Sechura (Piura), Sullana (Piura), Talara (Piura), Tambogrande (Piura), Trujillo (La Libertad), Tumbes (Tumbes), and Zarumilla (Tumbes).

[17] According to the 2019 Peruvian Ministry of Education School Census, this represents 33% of the high school student population in the Piura, Cajamarca, La Libertad, Lambayaque, Ancash and Tumbes regions, and 9% of the total high school enrollment in Peru. http://escale.minedu.gob.pe/padron-de-iiee.

[18] We excluded boys single-sex schools as well as schools outside Piura Region that could not be reached in a single bus trip.

[19] Power calculations where performed by the research team prior to the intervention. Based on a sample size of 5,450 students (109 clusters and 50 subjects per cluster), assuming an intra-cluster correlation of 0.05 with power of 80% we are able to detect an MDE of 0.19 standard deviations (with respect to the control group).

to treatment and control, respectively. Table A1 in the Appendix shows the baseline characteristics of students and schools by experimental group. As we can observe, our randomization was successful at achieving balance across control and treatment units observable characteristics.

The intervention. Role models visits took place between May and July 2018 and only targeted senior-year high school students. Our role models major in either i) civil engineering, or ii) industrial and systems engineering, or iii) mechanical and electrical engineering. They were 20 to 24 years old, and they were either engineering students in their fourth/fifth year of undergraduate studies or very recent graduates. In most cases, each treated school was visited by a single role model.[20]

It is worth mentioning that the role models prepared the presentation materials by themselves during several team-work sessions. They agreed on a general template, but adjustments were made to capture each role model's own experience as an engineering major. Role models also participated in a feedback session with UDEP faculty members before giving their talks. Most of the role models had previous experience in social events, group projects, and as volunteers in non-profit organizations and had developed strong communication skills.

Role models directly coordinated with UDEP Admissions Office on the date and time of the visits. The Admissions Office provided them with the school visits calendar and role models indicated the name of the person in charge of each talk. A lottery was used by the role models to assign the school visits conditional on each of them delivering approximately the same number of talks within and outside the Piura region. However, adjustments had to be made depending on role models' availability. On average, each role model delivered 5 talks.[21] Role models also received a monetary compensation, which was solely a function of the visited school's distance from Piura, and completely unrelated to performance in any sense. On average each role model received US$ 230 for their participation in the intervention.

[20] Two role models visited the treatment schools located in Trujillo and Tumbes. In these cases, only one role model did the presentation and the other accompanied her to the school visit. In seven other treatment schools, more than one role model gave the speech, which makes it difficult to identify the unique effect of each role model on the treated students. This happened because in these schools the number of sections was large and there were many senior-year students.

[21] Each role model gave between 3 and 7 talks.

It is important to highlight that in control schools, business continued as usual. That is, as in the last five years, these schools were visited by an UDEP admissions official who promoted all UDEP majors and admission mechanisms among senior high school students, without any mention of the role models intervention.

Content of the role model talks. During their presentations, which lasted approximately 20 minutes, role models used a set of slides highlighting the following facts: (i) gender differences in brain structure playing no role in determining males' and females' aptitude to pursue engineering majors, (ii) examples of contributions made by female engineers, (iii) definition of engineering as the art of solving problems and as a channel to change the world and make it better, (iv) statements aimed at deconstructing stereotypical views about engineering under the title "Beliefs or Reality?", (v) the experience of the role models at UDEP, and (vi) the relevance of creativity and ingenuity in engineering majors and the capability of girls to become engineers.[22] During and after their presentations, role models answered questions from students.

3 Data and empirical strategy

3.1 Data

Student follow-up survey. In November 2018, four to six months after the role models' talks were delivered, we conducted a follow-up survey in 101 out of the 109 schools included in the experimental sample.[23] Students' responses to the survey were anonymous. [2425]

The survey first asked students for their GPA scores in math, language

[22] In the talks the following statements were discussed: A person who wants to study engineering should be the top student in the class and a genius in mathematics, engineering is only for men, the engineers are boring, and women in engineering do not find jobs. Thumbnails of the slides shown during the school intervention are displayed in the Appendix. The full role models' presentation can be accessible throughout this link: https://drive.google.com/file/d/16VDemjA8wt2wY0-WGDMBHSMz-FycgLBp/view?usp=sharing.

[23] This included 54 out of 58 schools from the control group and 47 out of 51 schools from the treatment group. In 8 schools we could not conduct the follow-up survey because schools' authorities did not give us the necessary permission.

[24] Since we did not have access to the students' names or IDs, we are unable to match the survey data with UDEP's admissions or the Ministry of Education's administrative records.

[25] The survey was administered during class time; therefore, we have data on the students that were physically present at school on the day of the survey.

and science in the academic year that preceded our intervention; that is, when they were in 10th grade. We then asked students about the college major they would like to pursue, as well as several questions intended to measure self-confidence, gender beliefs, biases and perceptions. Regarding self-confidence, we asked students if they felt they have the abilities and skills needed to major in engineering at college. With respect to beliefs, biases and perceptions, we first asked students to imagine that they have two friends: "Javier", a boy; and "Lorena", a girl; and that both of them have a school GPA of 20 (the maximum possible score) in math and science. We then asked them which college major they would recommend to "Javier" and to "Lorena".[26] Similarly, we introduced to the students a hypothetical successful individual currently working in the engineering sector, and asked them whether that person was more likely to be a woman or a man. We also asked students to list at most five different engineering fields and collected information on students' expectations of the average monthly salary of a recent college graduate in engineering.

Finally, we collected data on parental demographic characteristics (i.e. age, education, working status, engineering background), siblings characteristics (i.e. number, gender, college major) and economic status (i.e. housing and other fixed assets ownership). Due to time, logistical and budget constraints, we did not survey students before the intervention. Therefore, we use the follow-up survey to capture information on students' pre-treatment characteristics. For such purpose, we will focus on socioeconomic variables which are unlikely to have changed over a 6 months period or have been affected by our intervention.

3.1.1 Data analysis

Balance in observable individual and school level characteristics. We collected information on 5,378 senior-year high school students; 56% (2,998) of them are female and 50% (2,704) are in the treatment group. In Table A1 Panel A in the Appendix, we present the balance tests for the combined sample of boys and girls. As we can see, average differences in observable characteristics between treatment and control individuals

[26] This question was designed to explore gender bias in STEM conditional on the same math and science skills. See for instance Bertrand & Mullainathan (2004).

are relatively small and not statistically significant.[27] Note that the self-reported 10th grade GPA in all subjects, which we will use to measure pre-treatment academic aptitude, is very close among treatment and control students. It can be pointed out that the treatment may have influenced students incentives to either reveal or conceal their 10th grade GPAs in the follow-up survey; so the fact that almost no differences are observed alleviates such concerns. Regarding other individual characteristics, on average students are 16 years old, have 2 siblings, their parents have 13 years of education and in 85% of the cases own their houses. About 95% of students have a working father and 68% have a working mother; while 15% and 3% have an engineer father and an engineer mother, respectively. Finally, the number of boys and girls in each quartile is also balanced across treatment and control schools.

Panel B in Table A1 in the Appendix compares the school level characteristics and finds that treated and control schools are similar on average. It is important to highlight that treated and control schools had almost the same performance in the 2015 national standardized evaluation for 8th graders; which corresponds to the year in which students in our cohort were evaluated. The results also support the use of self-reported GPAs as a reliable measure of students pre-treatment academic aptitude.

Gender differences in preferences, perceptions, beliefs and stereotypes. Here we focus exclusively on individuals in the control group to asses gender differences in terms of preferences, self-confidence, perceptions, beliefs and stereotypes. As shown in Table 1, while approximately 40% of boys in the control group preferred an engineering major, the number was only 14% for girls. The gap remains similar if we only focus on students in the top 10th grade math GPA quartile. In this case, more than 50% of boys stated engineering as their preferred college major, while just 20% of females did so (see Figure 1). The observed gap is likely connected to the fact that girls are less confident than boys in their skills and capabilities to pursue a career in engineering, (37% versus 59%), as it can be observed in Table 1.

[27] F-stat for joint significance is 1.11 (p-value is 0.358) and hence we can reject that all the variables can jointly explain the assignment to treatment. Nonetheless, in our estimations we will also control for baseline characteristics to improve the precision of the estimates.

Both boys and girls are more likely to consider a successful professional engineer to be a male. The percentage is nevertheless higher for boys (88% for boys and 61% for girls). Interestingly, nearly half of boys and girls (52% and 49% respectively) suggested engineering as a college major to "Lorena": a hypothetical female high school friend with the highest possible math and science GPA scores. Among girls in the top quartile of the math GPA distribution, this percentage is 58%, which is in clear contrast to the low proportion of them that prefer engineering majors. This suggests that while high math ability girls are likely to project another high math ability girl into an engineer career, they are less likely to do the same for themselves.[28] These findings strongly point to the relevance of interventions that can boost self-confidence among female students, particularly high math ability ones, to pursue engineering majors, such as the role models that we discuss in this paper.

3.2 Empirical strategy

We estimate the following Linear Probability Model (LPM):

$$Outcome_{isc} = \beta_0 + \beta_1 T_{isc} + \beta_2 female + \beta_3 female * T_{isc} + \beta_4 X_{isc} + \theta_c + \varepsilon_{isc} \quad (1)$$

where $Outcome_{isc}$ denotes the outcome of student i in school s and city c; T_{isc} is a dummy variable indicating whether the student's school located in city c has been selected to receive a role model visit, $female$ is a dummy variable that equals one for girls and zero for boys. We interact the female indicator with the treatment dummy to test for heterogenous treatment effects. We also control for student characteristics X_{isc} (including household background) and add city fixed effects (θ_c) to account for the fact that the randomization was stratified by city. Finally, in all our estimations standard errors are clustered at the school level.

The estimate on T_{isc} captures the Intent-to-Treat (ITT) effect of our intervention, since compliance with the initial random assignment was not perfect.[29] To deal with the non-compliance, we also estimate the

[28] Note also in Table 1 that students, both male and female, on average are able to list 4 types of engineering majors.

[29] Close to 12% of the schools assigned to the treatment group could not be visited by the role models. Non-compliance was mostly related to schools administrators not allowing the visit to take place as well

local average treatment effect (LATE) using random assignment as an instrument for actual treatment. The LATE estimates are very close to the ITT ones and are shown in the Appendix, Table A3.

A possible concern is that treated students may have talked about the role models talks contents with peers in control schools (i.e. friends in the neighborhood who attend a different school, or siblings attending different schools), which we expect to happen with low probability since the school or even the class is the unit within most peer interactions take place [Avvisati et al. (2014)]. Nevertheless, if spillovers do exist, our estimates could be interpreted as a lower bound of the actual impact of the intervention on students' career preferences.

4 Results

4.1 Effects on preferences for engineering majors

Table 2 presents the ITT intervention effect on students' preferences for engineering majors following the specification in equation (1). The first column shows the effect on students' preferences without controlling for covariates. Control variables are added gradually in columns 2 to 6. Notice that controlling for covariates does not significantly change either the sign or the size of the estimates. For the overall sample, the intervention does not have a statistically significant impact on boys' and girls' preferences for engineering programs.[30]

Regarding other covariates included in columns 2 to 6 in Table 2, several patterns are worth mentioning (See Table A2 in the Appendix). Firstly, in Peru engineering is clearly a male domain, and girls are 26 percentage points less likely to prefer engineering majors than boys (significant at 1%). Within-household peer effects are also likely to be present. Students with female siblings who are engineering students are 6 percentage points more likely to prefer engineering majors (significant at 5%). Similarly, those with a father engineer are 4 percentage points more like to state such preferences.

as last minute cancellations due to other school activities taking place.

[30] Also, Figure A8 in the Appendix shows the intent to treat estimates and the effect of other covariates on senior-year students' major preferences, while Figure A9 in the Appendix reports the ITT estimates and the effect of other covariates on students' perceptions.

Wealth also plays a role, and students who own their houses are more likely to prefer engineering majors by 3 percentage points. Finally, our results also point to comparative advantage in skills as a factor that is strongly related to preferences for majors. An additional point in grade 10th math GPA is related, *ceteris paribus*, to a 5 percentage points (significant at 1%) increase in the likelihood of preferring an engineering major. Similarly, an additional point in Language (Spanish) 10th grade GPA relates to a 2 percentage points (significant at 1%) decrease in the likelihood of preferring engineering as a major of study.

Given the recent findings in the role models and STEM career choices literature,[31] next we explore if our intervention had heterogeneous effects for different ranges of the students' math ability distribution, as measured by their self-reported grade 10th math GPA. Then we look for local role model effects. That is, if role models effects are stronger among students who reside closer to UDEP historical area of influence.

Heterogeneous effects as a function of math ability. To shed light on how our role models intervention might have impacted students differently depending on their math aptitude, we split the sample into four groups or quartiles as a function of their math GPA in the school year preceding the intervention (10th grade).[32] As shown in Table A1 Panel A in the Appendix, the number of girls and boys in each quartile is balanced across treatment and control gorups.[33]

Figure 1 shows the proportion of senior-year high school students who listed engineering as their most preferred college major, separately by gender and over the quartiles of pre-treatment math GPA. As we can observe, students in the top math GPA quartiles find engineering majors more attractive. We can also observe that our intervention seems to have a positive impact

[31]Several papers have explored heterogeneous effects of exposure to role models on educational outcomes such as Kipchumba et al. (2021), Lim & Meer (2020), Porter & Serra (2020), and Breda et al. (2020).

[32]These four groups or quartiles are constructed based on the students self-reported 10th grade math GPA. Considering a 20-point grading scale, students in the fourth, highest, quartile have a baseline math GPA in 10th grade higher than 16, those in the third quartile have baseline math scores of 16, those in the second lowest quartile have baseline math scores of 14 or 15, and finally those in the first, lowest, quartile report baseline math scores less than or equal to 13. Moreover, since baseline self-reported GPA math scores are discrete, the quartiles constructed do not have similar sizes: 32% of the observations lay in the first or lowest quartile, 34% of the observations lay in the second quartile, 14% of the observations lay in the third quartile, and 20% of the observations lay in the upper or top quartile.

[33]With the exception of boys in Q3 which is slightly higher in treatment relative to the control group.

only on girls in the top quartile of the math GPA distribution. For this particular subgroup, the probability of preferring engineering as a college major increases by 7.3 percentage points (significant at 10%) if their school was assigned to the role model intervention. To put this in perspective: this result represents a 36 percent increase from the 20 percent baseline level and conveys a 18.6 percent reduction in the gender gap. There is no evidence in Figure 1 of any intervention effect among boys in the upper math GPA quartiles. Note that these boys are already strongly committed to engineering majors: more than 50% of them indicated preferences for an engineering field. In social and cultural contexts in which high math ability boys are already committed to pursuing an engineering major, a soft role model intervention that mainly targets females is unlikely to have an impact on their preferences.

Table 3 further explores the ITT intervention effects for the sub-sample of students in the upper quartile of baseline GPA math scores. As we can observe, in all model specifications the ITT estimated coefficients for females in the top math quartile are positive and statistically significant at the 5% level; while the estimated ITT coefficients among boys are very close to zero and not statistically significant. Note however that the coefficients for the interaction term among treatment and female status are not statistically significant (except for column 4 at the 10% level); so we cannot reject the null hypothesis of no different ITT effects across genders.

While Figure 1 clearly indicates that boys in the upper math quartiles are not affected by the intervention; there seems to be a positive, although not statistically significant, effect among boys in the lower quartiles. To explore this further, the estimations in Table 4 focus on boys in the two lowest math GPA quartiles. While the ITT estimates are always positive, in general they are not statistically significant; with the exception of those corresponding to the specifications in columns II and III in Panel B (which focus on the second lowest GPA math quartile).

Finally, there may be some concerns given our use of self-reported math scores as a proxy for ability. In particular, the intervention itself may have influenced how students reported their baseline math scores. For example, social desirability bias may have led students in the treatment group to inflate their scores relative to those in control schools. As we discussed before, there are no statistically significant differences in terms of self-reported 10th grade among treated and control individuals. Nevertheless, to examine this further, we compare the distribution of reported math scores (from the survey) to actual math scores using administrative data.[34] As can be seen in Figure A10 and Table A13 in the Appendix, students tend to inflate their math scores. The average school inflation is 1.42 points. However, there is no difference in over-reporting between treatment and control schools (1.43 for treatment and 1.40 for control). Further, we find that girls inflate less than boys. It is possible that this difference in grade inflation affects the composition of quartiles. However, we find that our results remain unchanged if we use gender-specific distributions to create quartiles.[35]

Heterogeneous effects as a function of geographical location. During their talks, role models clearly stated their UDEP connection. In this sense, they may have been more effective (i.e. better at capturing the student attention) in schools within areas in which our partner university has a relatively high reputation and/or recognition. In fact, UDEP is recognized as the most prestigious university in the Piura region, and this influence and prestige also extends to the neighboring regions of Tumbes (to the North) and Lambayeque (to the South). This is confirmed by the fact that in the last 5 years, 80% to 85% of incoming UDEP's students are from Piura, and close to 95% are from the three above-mentioned regions. On the other hand, the regions of La Libertad, Cajamarca, and Ancash, which are geographically distant from Piura, have their own established local and regional universities.[36]

In Figure 2 we restrict our sample to schools within the Piura region and observe that the ITT effect for girls in the top math quartile becomes stronger (15.7 percentage points) and highly statistically significant at the 1% level. Taking this evidence into account, in Table 5 we explore the

[34] All schools submit Grade 10 scores to the Ministry of Education. We have access to this data and restricted it to schools in our sample to construct the actual distribution of math scores. However, the student identifier in this data set is anonymized because of which we are unable to use a student's actual math scores in our estimation.

[35] Results available upon request.

[36] For example, in La Libertad region, Universidad Privada del Norte, Universidad Antenor Orrego, and Universidad Nacional de Trujillo are generally identified as the three most prestigious regional universities.

ITT intervention effects among high-ability students in schools located in Piura only, while in Table 6 we perform a similar analysis adding the neighbouring regions of Tumbes and Lambayeque. Our findings indicate that our intervention seems to have been more effective at steering high math skilled girls (upper quartile) towards engineering fields in schools located geographically close to UDEP. Treated girls in the top math GPA quartile and enrolled in Piura schools are 14.1 percentage points more likely to prefer engineering (78% increase from a baseline of 18%) than similar girls in the control group [See Table 5, column 1]. Note that the estimate size remains relatively stable after the inclusion of different covariates and that the interaction coefficient term between the treatment and female indicators is always statistically significant at the 1% level. Hence, for the Piura region sample, we can clearly reject the null hypothesis of no difference in treatment effects between boys and girls. When we constrain the sample to the three main regions in terms of UDEP influence (Piura, Lambayeque and Tumbes) in Table 6, the ITT estimates for females are slightly smaller that those in Table 5, but remain statistically significant at the 1% level.

In Table 7 and Table 8, we explore the ITT effects among students in the two lowest math quartiles, first for the Piura region only and then for the Piura, Lambayeque and Tumbes regions altogether. As in Table 4, the ITT among boys is always positive (between 6 and 9 percentage points) but statistically significant, generally at the 10% level, only in some specifications. Note that the estimated effect for girls in this case is very close to zero and not statistically significant. Since role models emphasized that a person does not have to be a math genius to major in engineering, and that skills like imagination and creativity are also important to pursue engineering careers, it seems possible that some low math ability boys may have adjusted their engineering preferences as a result of this specific message. Nevertheless, given the weak nature of the evidence in this case, we believe these results should be treated with caution.

Table 9 summarizes the ITT estimates for our role model interventions separately by gender, geographical location and 10th grade math GPA quartile. In Panel A of Table 9, the ITT estimates correspond to the full sample, while in panel B we restrict the analysis to schools in the region of Piura and adjacent regions of Tumbes and Lambayeque. Overall, our intervention increased the likelihood that a female senior-year high school student in the upper math quartile who resides geographically close to UDEP, stated engineering as her most preferred major. No effects for female students in the 1st, 2nd, and 3rd quartile were found in any specification.[37] Moreover, we also find some, although week, evidence suggesting that female role models may have also affected the engineering major preferences of low math ability male students.

4.2 Self-confidence, beliefs and stereotypes

To shed light on the mechanisms behind our intervention, in the follow-up survey we presented students with several statements intended to measure self-confidence and gender stereotypes. We begin this analysis with Table 10, which focuses on students' self-confidence in their own skills and aptitude to pursue engineering majors. We observe that treated girls in the top quartile of the math score distribution are 12.5 percentage points (significant at 5%) more likely to indicate that they do have the necessary skills and aptitude to major in engineering. This specific result suggests that role models were a source of inspiration, positively influencing these girls' self-confidence, which, as shown before, resulted in an increased preference for studying engineering.

Interestingly, Table 10 also shows that high math ability treated boys appear to be less confident in their aptitude and skills to pursue an engineering major. As pointed before, one of the key pieces of information in the role models talks was that you don't need to be a mathematical genius to major in engineering, and that other skills, such as imagination and ingenuity, are also relevant. This message may have influenced the perceptions of these boys about the role of math skills alone to succeed in engineering majors. Note however that the adjustment in perceptions did not affect their stated preferences. In a social context in which high math ability boys are expected to be engineers, this extra piece of information and

[37]We also calculated probit marginal effects, which are similar to the OLS estimates and can be provided upon request.

the subsequent adjustment in perceptions, is likely not to be adequate to fully switch them out of engineering majors. In any case, such issues should be kept in mind when designing similar role model interventions. Also interestingly, in the case of boys in the two lowest math ability quartiles, the results in Table 10 suggest a 4 to 5 percentage points increase in the self-confidence outcome; however, it is not statistically significant. Once again, the key message on aptitudes other than math ability to succeed as an engineer may be playing a role in this case. Overall, boys within the UDEP's catchment area seem to have been carefully listening to the information provided in the talks.

In Tables 11 and 12, we evaluate whether or not the role models affected gender beliefs, biases and stereotypes. In our follow-up survey, we described a person who happens to be a successful engineer and asked students whether they thought that this person was more likely to be male or female. We constructed an indicator that took the value of one when the student responded that the person was more likely to be male, and zero otherwise. Table 11 presents the results related to this question. In general, the coefficients for all females quartiles have the expected sign: treated girls are less likely to indicate that the successful engineer is male, but the estimated coefficients are relatively small and not statistically significant. The estimated coefficients for boys are also negative, but smaller in absolute size than the female ones and not statically significant. We speculate that a lasting impact on gender beliefs, biases and stereotypes, possibly needs a longer than 20 minutes intervention in countries like Peru.

Also regarding gender stereotypes, we presented students in our sample with two hypothetical high school students: a female named "Lorena" and a male named "Javier", and describe both as high math and high science ability individuals. We then asked students to suggest a major to each of them. The outcome variable takes the value of one if the student recommended an engineering major to "Lorena". The results in Table 12 indicate that treated girls were not more likely than control ones to recommend engineering majors to "Lorena". It is nevertheless important to note that close to 60% of top math ability girls in the control group are already recommending engineering to the hypothetical high math ability girl; but very few are applying this recommendation to themselves. In other words, self-confidence seems to be the critical issue; and as we have shown before, it is self-confidence what is primarily being impacted by our role models. In the case of treated boys, Table 12 indicates that those in the second-lowest quartile residing within UDEP catchment area were more likely to suggest an engineering major to our hypothetical female student. As mentioned before, the fact that role models strongly emphasized that women can also succeed as engineers may be the driving factor behind the boys results. Clearly boys seem to have been paying attention to the information delivered.

Although the role models did not provide either any information about earnings associated with engineering careers (as they wanted it to be about abilities) or an exhaustive list of engineering specializations, in the follow-up survey we asked students related questions as we wanted to see if this intervention made them seek out more information on engineering majors. In this case, we find some statistically significant effects for girls in the top math quartile and boys in the second lowest math quartile; however, the size of the effects is relatively small. As we can see in Tables 13 and 14, treated high math ability girls listed 0.2 less engineering fields than those in the control group (who listed 4.7); while the salary expectations of boys in the second lowest math quartile increased just by 1% relative to the control group.

4.3 Effects on Types of Engineering

Our role models were from one of the following three engineering majors: industrial, civil and mechanical-electrical, which are actually the only three engineering specializations offered at UDEP. During their presentations, the role models emphasized their own major as well as their connection with UDEP. Given this context, role models may have been more effective at promoting their own engineering major or UDEP engineering majors in general.[38] To test for this possibility, we create a binary outcome variable

[38]In this regard, it is important to emphasize that while UDEP is the leading university in the area, there are several other universities, including the public National University of Piura, which offer a wide range of engineering majors in addition to UDEP's ones. Hence, the students' major preferences are unlikely to be fully restricted by UDEP

which equals one if the student stated as her/his preferred engineering major to be any of the role models' ones and zero otherwise. As shown in Panel A in Table 15, girls in the top math ability quartile are 10.4 percentage points (significant at 5%) more likely to list one of the role models' engineering majors. Within UDEP's catchment area, the likelihood of preferring these three engineering majors increased by 13.4 percentage points (significant at 1%) for high-ability girls, as shown in Panel B of the same table. Note also that there is no statistically significant effect among boys, and the estimated coefficients in this case are relatively small. These results suggest that treated female students are clearly connected with the specific experience of their role models, and confirm that role models were a source of inspiration. The results also provide important lessons for the design of role model interventions. STEM role models seem to be more effective at influencing career paths that are closely related to their own experiences.

4.4 More on local effects: school distance to UDEP

In this section we provide additional evidence on whether students in schools located geographically close to UDEP were more likely to be encouraged to pursue engineering fields by our role models, but also on whether or not the effects in UDEP proximate schools are different from those in far-away ones. Using longitude and latitude coordinates, we calculate the distance in kilometers from the schools in our sample to UDEP. Using the estimated distances, Tables A6-A11 in the Appendix show that geographical closeness matters. Girls in the top GPA math quartile are 17.2 percentage points (significant at 1%) more likely to prefer engineering after a role model exposure if they come from a school located below the median distance (less than 43 km) from UDEP (Column 6, Table A6 in the Appendix). Moreover, the effect for schools above the median distance is close to zero and we can reject the null hypothesis of equal ITT effects among nearby and far-away schools. The analysis for boys in the bottom quartiles of math scores is presented in Table A7 in the Appendix

engineering academic offer.

and leads to similar conclusions.[39] Overall, these results confirm that the relevance of UDEP's role models is higher in the geographical areas where UDEP historically has had a stronger influence.

4.5 Effects on Other Majors

In the previous section, we found that, relative to the control group, treated high math ability female students increased their preferences for engineering. In this section we explore how the intervention affected students' preference for both non-STEM majors and STEM majors other than engineering.

As we can observe in Table 16, the intervention clearly affected the preferences for non-STEM majors among high math aptitude girls. Treated girls in the top math quartile are less likely to report that they will choose a non-STEM major.[40]Also note that the absolute value of the estimated coefficients are relatively similar to those observed for high math aptitude girls in Table 9. This clearly indicates that our intervention is shifting the preferences of high math aptitude girls from non-stem majors to engineering ones. There is also some, though weaker, evidence in this table suggesting that the intervention is doing the same for boys in the lowest math ability quartiles within UDEP's catchment area. In a similar fashion, we also investigate if students in our intervention were more likely to prefer STEM fields other than engineering (i.e. Life-Science, Mathematics, Statistics, Physics) as a consequence of being exposed to a young engineer role model. We do not find neither sizable nor statistically significant estimates in this case. This quite likely due to the extremely low share of students who prefer STEM majors different from engineering in Peru.[41]

[39]In Tables A8-A11 in the Appendix we evaluate the effect on different subgroups of individuals based on location and math skills. The results seem to be robust for different subgroups of students. The liking for engineering increases after the intervention in nearby schools.

[40]Non-STEM majors affected by the intervention are Business Administration, Economics, Communication, Accounting, Marketing, Law, Architecture, Medicine, Psychology.

[41]These results are available upon request.

5 Robustness checks

5.1 Alternative measures of ability: Science and math

In our baseline estimations, we explored differential ITT effects as a function of students' math ability only, which is generally regarded an indicator of students' capacity to major in engineering. In this section, in addition to math scores, we also consider 10th grade science scores, as competence in science may also be an indicator of the student aptitude to major in engineering. We therefore construct a binary indicator equal to one if the student ranked in the top quartile in both math and science, and zero, otherwise. As expected, the ITT effect in this case is positive and statistically significant for female students in the top, math and science, quartile and who reside within UDEP's catchment area (See Appendix Table A4). These girls are 21 percentage points (significant at 1%) more likely to prefer engineering as a result of our role models intervention.

5.2 ECE math scores

While our balance tests confirm that treatment and control schools are of similar academic quality, the fact that we are not using standardized scores to define our math ability quartiles may be a cause of concern for some readers. In order to alleviate these concerns, we again estimate the specifications in Table 6 using the school average math section performance in the *Evaluación Censal de Estudiantes* (ECE), which is a standardized national examination administered annually to 8th graders, as a comtrol variable. As students in our sample were in the 8th grade in 2015, the 2015 ECE results allow us to control for the academic quality of our school cohorts. The estimations results are shown in Table A5 in the Appendix. As it can be observed, the results are very similar to those in Table 6.

6 Conclusion

Using experimental evidence from an RCT in Peru that exposed senior high school students to young female engineers (college seniors or recent graduates), we show that role models are important as they are able to shift the preferences of some of the subjects. Interestingly, our evidence also suggests that both male and female high school students carefully listen to the message delivered by the role models.

We find that treated high school girls in the highest math ability quartile are more likely to prefer engineering majors, as do treated boys in the two lowest math quartiles. Our evidence shows that the role models were able to inspire these girls by changing their self-confidence regarding their own skills and aptitudes for successfully pursuing engineering majors. They also affected the preferences of low math ability boys by telling them that engineering is not just about math ability, but that creativity and ingenuity are also important.

We also find that while role models matter, the context in which they intervene critically influences their effectiveness. Geographical proximity is important since the role model effects in our study are stronger among students who attend schools located in the area where UDEP has historically had a stronger influence. This is akin to arguing that role models from Virginia Tech will be more effective in regions around Virginia Tech rather than in places around Georgia Tech. Also importantly, we show that role models are more effective at influencing the preferences for career paths that are closely related to their own experience, i.e., if we want girls to pursue civil engineering, the role models who have done civil engineering will be more effective.

All the above suggest that while they are effective and relatively low-cost, role model interventions need to be carefully designed to maximize their impact. Firstly, it is important to pay careful attention to their message content and potential audience. While female role model interventions related to STEM fields primarily target girls, boys may also react to some specifics of the message. Secondly, an important message for the design of role models programs is that the implementation context should be carefully evaluated. Not everyone can be an effective role model in every situation or at promoting any STEM field.

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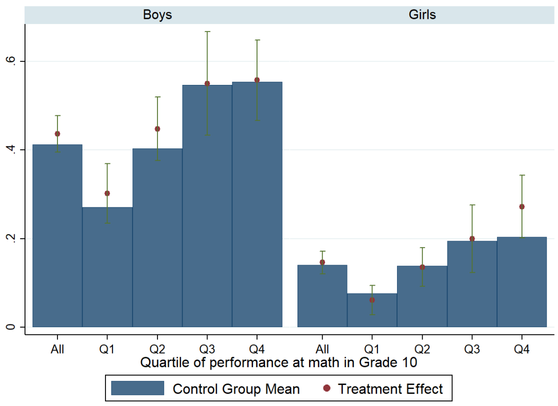
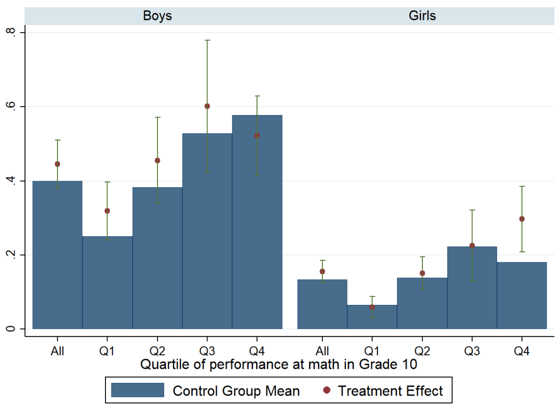
Figures and Tables

Figure 1: Senior-year high school students- preference for engineering by student gender and quartile of baseline math score



Notes: The figure shows the fraction of senior-year high school students (grade 11) who stated they would like to study Engineering after graduating from high school, for boys (left panel) and girls (right panel) separately. The blue bars indicate the mean among all students in the control group and the separate means by quartile of final course grade on math in grade 10. The red solid dots show the estimated treatment effects with 95% confidence intervals denoted by vertical capped bars.

Figure 2: Senior-year high school students- preference for engineering by student gender and quartile of baseline math score: only Piura



Notes: The figure shows the fraction of senior-year high school students (grade 11) who stated they would like to study Engineering after graduating from high school, for boys (left panel) and girls (right panel) separately. The sample includes only students in schools located in Piura. The blue bars indicate the mean among all students in the control group and the separate means by quartile of final course grade on math in grade 10. Red solid dots show the estimated treatment effects with 95% confidence intervals denoted by vertical capped bars.

Table 1: Difference in preferences for engineering and perceptions: by gender

Sample:	(1) Boys	(2) Girls	(3) Diff
Prefer engineering	0.405	0.139	0.266***
	(0.015)	(0.009)	(0.017)
Male_success	0.883	0.609	0.274***
Successful engineer is male	(0.010)	(0.013)	(0.016)
Self_confidence	0.585	0.367	0.219***
Consider to have needed skills to succeed in engineering	(0.015)	(0.012)	(0.019)
University_study	0.670	0.711	-0.041**
Plan to study at university	(0.014)	(0.012)	(0.018)
lorena_eng	0.520	0.492	0.028
Recommended engineering to Lorena	(0.015)	(0.013)	(0.020)
count_eng	4.323	4.403	-0.081**
Number of engineering majors listed	(0.031)	(0.023)	(0.037)

Notes: This table reports the means for different outcomes of a test of equality by gender. Standard errors are reported in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 2: The effect of exposure to role models on students' preference for engineering

Dep. Variable:	**Prefer Engineering**					
Sample:	Full	Full	Full	Full	Full	Full
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.036	0.036	0.035	0.034	0.016	0.018
	(0.025)	(0.026)	(0.026)	(0.024)	(0.024)	(0.024)
Female	-0.263***	-0.265***	-0.266***	-0.265***	-0.258***	-0.261***
	(0.018)	(0.018)	(0.018)	(0.017)	(0.019)	(0.018)
Interaction	-0.023	-0.024	-0.024	-0.024	-0.008	-0.008
(Treatment*female)	(0.027)	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
ITT female: Treatment + Interaction	0.013	0.011	0.011	0.010	0.008	0.010
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Number of observations (N)	5156	4872	4856	4783	4639	4580
Adjusted R^2	0.105	0.107	0.109	0.114	0.158	0.161
Mean Dv (Treatment==0)	0.14	0.14	0.14	0.14	0.14	0.14

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering for the full sample of students who answered the survey. Column 1 reports the ITT estimates without covariates. In columns 2 to 6 we gradually add the following controls: has an engineering parent, owns house, parental education FE, baseline scores in 10th grade, age and having an engineer sibling. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 3: The effect of exposure to role models on students' preference for engineering (high ability students)

Dep. Variable:	Prefer Engineering					
Sample:	4th Q math	4th Q math	4th Q math	4th Q math	4th Q math	4th Q math
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.003	0.005	0.001	-0.004	-0.006	-0.002
	(0.043)	(0.047)	(0.047)	(0.046)	(0.049)	(0.049)
Female	-0.335***	-0.338***	-0.338***	-0.331***	-0.309***	-0.307***
	(0.031)	(0.031)	(0.031)	(0.030)	(0.037)	(0.038)
Interaction	0.083	0.082	0.083	0.091*	0.096	0.093
(Treatment*female)	(0.055)	(0.054)	(0.054)	(0.054)	(0.059)	(0.059)
ITT female: Treatment + Interaction	0.080**	0.087**	0.084**	0.088**	0.090**	0.091**
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Number of observations (N)	1014	960	957	945	942	939
Adjusted R^2	0.117	0.126	0.128	0.126	0.133	0.136
Mean Dv (Treatment==0)	0.20	0.20	0.20	0.20	0.20	0.20

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering for high ability students (fourth quartile of baseline math scores) , who answered the survey. Column 1 reports the ITT estimates without covariates. In columns 2 to 6 we gradually add the following controls: has an engineering parent, owns house, parental education FE, baseline scores in 10th grade, age and having an engineer sibling. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: The effect of exposure to role models on students' preference for engineering (low ability students)

Dep. Variable:	Prefer Engineering					
Panel A:	1st Q math (1)	1st Q math (2)	1st Q math (3)	1st Q math (4)	1st Q math (5)	1st Q math (6)
Treatment	0.0323	0.0309	0.0330	0.0390	0.0224	0.0196
	(0.0333)	(0.0369)	(0.0368)	(0.0354)	(0.0350)	(0.0355)
Female	-0.190***	-0.194***	-0.193***	-0.201***	-0.192***	-0.195***
	(0.0243)	(0.0269)	(0.0268)	(0.0254)	(0.0247)	(0.0251)
Interaction	-0.0478	-0.0504	-0.0545	-0.0543	-0.0389	-0.0387
	(0.0379)	(0.0413)	(0.0410)	(0.0398)	(0.0397)	(0.0398)
ITT female: Treatment + Interaction	-0.016	-0.020	-0.021	-0.015	-0.017	-0.019
Number of observations (N)	1,606	1,504	1,498	1,472	1,462	1,437
Adjusted R^2	0.086	0.086	0.088	0.104	0.117	0.118
Mean Dv (Treatment==0)	0.08	0.08	0.08	0.08	0.08	0.08
Panel B:	2nd Q math (1)	2nd Q math (2)	2nd Q math (3)	2nd Q math (4)	2nd Q math (5)	2nd Q math (6)
Treatment	0.0621	0.0761*	0.0733*	0.0683	0.0624	0.0665
	(0.0435)	(0.0437)	(0.0437)	(0.0427)	(0.0429)	(0.0418)
female	-0.258***	-0.254***	-0.256***	-0.257***	-0.246***	-0.254***
	(0.0359)	(0.0355)	(0.0357)	(0.0354)	(0.0353)	(0.0360)
Interaction	-0.0531	-0.0666	-0.0638	-0.0642	-0.0685	-0.0655
(Treatment*female)	(0.0477)	(0.0472)	(0.0475)	(0.0470)	(0.0475)	(0.0478)
ITT female: Treatment + Interaction	0.00896	0.00945	0.00944	0.00409	-0.00615	0.00109
Number of observations (N)	1,690	1,613	1,609	1,591	1,582	1,558
Adjusted R^2	0.114	0.115	0.116	0.124	0.138	0.146
Mean Dv (Treatment==0)	0.14	0.14	0.14	0.14	0.14	0.14
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences. Sample is restricted to low ability students in the first or second quartile of baseline math scores, who answered the survey. Column 1 reports the ITT estimates without covariates. In columns 2 to 6 we gradually add the following controls: has an engineering parent, owns house, parental education FE, baseline scores in 10th grade, age and having an engineer sibling. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: The effect of exposure to role models on students' preference for engineering for high ability students in Piura schools

Dep. Variable:	Prefer Engineering					
Sample:	4th Q math (1)	4th Q math (2)	4th Q math (3)	4th Q math (4)	4th Q math (5)	4th Q math (6)
Treatment	-0.036	-0.030	-0.037	-0.031	-0.026	-0.012
	(0.056)	(0.058)	(0.056)	(0.057)	(0.059)	(0.057)
Female	-0.360***	-0.362***	-0.361***	-0.352***	-0.316***	-0.296***
	(0.045)	(0.045)	(0.043)	(0.042)	(0.048)	(0.048)
Interaction	0.177**	0.179**	0.177***	0.176**	0.171**	0.153**
(Treatment*female)	(0.069)	(0.068)	(0.064)	(0.067)	(0.070)	(0.071)
ITT female: Treatment + Interaction	0.141***	0.148***	0.140***	0.145***	0.144***	0.141***
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Number of observations (N)	549	516	514	511	510	507
Adjusted R^2	0.123	0.136	0.144	0.132	0.133	0.143
Mean Dv (Treatment==0)	0.18	0.18	0.18	0.18	0.18	0.18

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to high ability students (fourth quartile of baseline math scores) in schools located in Piura, who answered the survey. Column 1 reports the ITT estimates without covariates. In columns 2 to 6 we gradually add the following controls: has an engineering parent, owns house, parental education FE, baseline scores in 10th grade, age and having an engineer sibling. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 6: The effect of exposure to role models on students' preference for engineering for high ability students in Piura/Lambayeque/Tumbes schools

Dep. Variable:	Prefer Engineering					
Sample:	4th Q math (1)	4th Q math (2)	4th Q math (3)	4th Q math (4)	4th Q math (5)	4th Q math (6)
Treatment	-0.041	-0.039	-0.042	-0.039	-0.049	-0.043
	(0.049)	(0.049)	(0.049)	(0.049)	(0.051)	(0.050)
Female	-0.374***	-0.373***	-0.371***	-0.370***	-0.358***	-0.354***
	(0.032)	(0.033)	(0.032)	(0.033)	(0.039)	(0.042)
Interaction	0.163***	0.162***	0.162***	0.169***	0.179***	0.174***
(Treatment*female)	(0.058)	(0.057)	(0.056)	(0.058)	(0.064)	(0.065)
ITT female: Treatment + Interaction	0.122***	0.124***	0.120***	0.129***	0.130***	0.131***
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Number of observations (N)	744	706	704	697	694	691
Adjusted R^2	0.135	0.140	0.141	0.133	0.134	0.141
Mean Dv (Treatment==0)	0.17	0.17	0.17	0.17	0.17	0.17

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to high ability students (fourth quartile of baseline math scores) in schools located in Piura/Lambayeque/Tumbes, who answered the survey. Column 1 reports the ITT estimates without covariates. In columns 2 to 6 we gradually add the following controls: has an engineering parent, owns house, parental education FE, baseline scores in 10th grade, age and having an engineer sibling. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 7: The effect of exposure to role models on students' preference for engineering (low ability students) in Piura schools

Dep. Variable:	Prefer Engineering					
Panel A:	1st Q math (1)	1st Q math (2)	1st Q math (3)	1st Q math (4)	1st Q math (5)	1st Q math (6)
Treatment	0.070	0.068	0.066	0.073*	0.058	0.051
	(0.042)	(0.047)	(0.046)	(0.043)	(0.044)	(0.044)
Female	-0.181***	-0.184***	-0.186***	-0.199***	-0.194***	-0.198***
	(0.033)	(0.038)	(0.037)	(0.034)	(0.035)	(0.034)
Interaction	-0.076	-0.080	-0.082	-0.078	-0.058	-0.053
(Treatment*female)	(0.048)	(0.053)	(0.052)	(0.050)	(0.051)	(0.050)
ITT female: Treatment + Interaction	-0.006	-0.012	-0.016	-0.005	0.000	-0.002
Number of observations (N)	1033	964	960	943	937	919
Adjusted R^2	0.099	0.104	0.108	0.129	0.138	0.136
Mean Dv (Treatment==0)	0.06	0.06	0.06	0.06	0.06	0.06
Panel B:	2nd Q math (1)	2nd Q math (2)	2nd Q math (3)	2nd Q math (4)	2nd Q math (5)	2nd Q math (6)
Treatment	0.0824	0.0986*	0.0957	0.0837	0.0893	0.0932*
	(0.0591)	(0.0589)	(0.0585)	(0.0562)	(0.0579)	(0.0555)
female	-0.238***	-0.225***	-0.229***	-0.234***	-0.212***	-0.220***
	(0.0499)	(0.0500)	(0.0497)	(0.0481)	(0.0493)	(0.0503)
Interaction	-0.0620	-0.0723	-0.0679	-0.0645	-0.0824	-0.0826
(Treatment*female)	(0.0612)	(0.0607)	(0.0604)	(0.0586)	(0.0597)	(0.0610)
ITT female: Treatment + Interaction	0.0204	0.0263	0.0278	0.0192	0.00695	0.0106
Number of observations (N)	1,128	1,073	1,070	1,055	1,051	1,031
Adjusted R^2	0.103	0.099	0.100	0.109	0.132	0.144
Mean Dv (Treatment==0)	0.14	0.14	0.14	0.14	0.14	0.14
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences. Sample is restricted to low ability students (first or second quartile of baseline math scores) in schools located in Piura, who answered the survey. Column 1 reports the ITT estimates without covariates. In columns 2 to 6 we gradually add the following controls: has an engineering parent, owns house, parental education FE, baseline scores in 10th grade, age and having an engineer sibling. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 8: The effect of exposure to role models on students' preference for engineering (low ability students) in Piura/Lambayeque/Tumbes schools

Dep. Variable:			Prefer Engineering			
Panel A:	1st Q math (1)	1st Q math (2)	1st Q math (3)	1st Q math (4)	1st Q math (5)	1st Q math (6)
Treatment	0.066*	0.062	0.064*	0.077**	0.064*	0.059
	(0.035)	(0.038)	(0.038)	(0.036)	(0.036)	(0.036)
Female	-0.178***	-0.186***	-0.186***	-0.194***	-0.184***	-0.187***
	(0.025)	(0.028)	(0.028)	(0.026)	(0.025)	(0.025)
Interaction	-0.078*	-0.079*	-0.083*	-0.085**	-0.073*	-0.070*
(Treatment*female)	(0.041)	(0.043)	(0.043)	(0.042)	(0.042)	(0.041)
ITT female: Treatment + Interaction	-0.012	-0.017	-0.019	-0.008	-0.009	-0.012
Number of observations (N)	1265	1183	1178	1158	1151	1132
Adjusted R^2	0.097	0.103	0.106	0.124	0.131	0.131
Mean Dv (Treatment==0)	0.07	0.07	0.07	0.07	0.07	0.07
Panel B:	2nd Q math (1)	2nd Q math (2)	2nd Q math (3)	2nd Q math (4)	2nd Q math (5)	2nd Q math (6)
Treatment	0.058	0.071	0.068	0.060	0.059	0.064
	(0.052)	(0.051)	(0.051)	(0.049)	(0.050)	(0.048)
female	-0.248***	-0.241***	-0.242***	-0.245***	-0.233***	-0.239***
	(0.042)	(0.041)	(0.041)	(0.041)	(0.040)	(0.041)
Interaction	-0.041	-0.048	-0.045	-0.043	-0.054	-0.053
(Treatment*female)	(0.055)	(0.053)	(0.054)	(0.053)	(0.053)	(0.054)
ITT female: Treatment + Interaction	0.0168	0.0227	0.0230	0.0172	0.00557	0.0114
Number of observations (N)	1,357	1,294	1,291	1,274	1,266	1,246
Adjusted R^2	0.098	0.094	0.095	0.106	0.123	0.135
Mean Dv (Treatment==0)	0.14	0.14	0.14	0.14	0.14	0.14
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences. Sample is restricted to low ability students (first or second quartile of baseline math scores) in schools located in Piura/Lambayeque/Tumbes, who answered the survey. Column 1 reports the ITT estimates without covariates. In columns 2 to 6 we gradually add the following controls: has an engineering parent, owns house, parental education FE, baseline scores in 10th grade, age and having an engineer sibling. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 9: The effect of exposure to role models on students' preference for engineering by quartile of math performance

Outcome: Prefer Engineering	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
Q1	0.076	-0.019	0.016	0.271	0.020	0.035	1437	0.333
Q2	0.138	0.001	0.025	0.403	0.067	0.042	1558	0.174
Q3	0.194	-0.002	0.039	0.546	-0.069	0.066	646	0.347
Q4	0.205	0.091**	0.042	0.554	-0.002	0.049	939	0.121
Panel B: Main Regions								
Q1	0.068	-0.012	0.016	0.251	0.059	0.036	1132	0.093
Q2	0.138	0.011	0.027	0.389	0.064	0.048	1246	0.329
Q3	0.195	0.011	0.042	0.527	-0.008	0.072	515	0.821
Q4	0.175	0.131***	0.044	0.573	-0.043	0.050	691	0.010

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for engineering, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 10: The effect of exposure to role models on students' perceptions by quartile of math performance: self-confidence

Outcome: Self-confidence	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
Q1	0.197	0.002	0.035	0.391	0.045	0.042	1509	0.383
Q2	0.346	0.022	0.038	0.564	0.045	0.041	1612	0.635
Q3	0.488	0.045	0.052	0.773	-0.062	0.069	658	0.205
Q4	0.580	0.044	0.050	0.835	-0.090**	0.044	960	0.070
Panel B: Main Regions								
Q1	0.194	0.003	0.040	0.395	0.034	0.050	1190	0.588
Q2	0.343	0.034	0.041	0.565	0.055	0.046	1290	0.710
Q3	0.515	0.047	0.058	0.740	0.019	0.084	522	0.788
Q4	0.551	0.125**	0.054	0.853	-0.116**	0.053	708	0.006

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' self-confidence in their aptitude and skills to pursue an engineering major, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 11: The effect of exposure to role models on students' perceptions by quartile of math performance: success exclusively for men in the sector

Outcome: Male Successful	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
Q1	0.633	-0.037	0.040	0.391	-0.040	0.032	1400	0.951
Q2	0.605	-0.050	0.039	0.564	0.011	0.029	1524	0.164
Q3	0.629	0.017	0.050	0.773	-0.004	0.050	624	0.774
Q4	0.557	-0.047	0.047	0.835	0.004	0.041	894	0.375
Panel B: Main Regions								
Q1	0.651	-0.061	0.044	0.395	-0.026	0.036	1126	0.565
Q2	0.609	-0.045	0.043	0.565	-0.011	0.032	1233	0.473
Q3	0.648	-0.007	0.056	0.740	-0.007	0.063	499	0.999
Q4	0.567	-0.009	0.055	0.853	0.014	0.048	674	0.723

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' perceptions of males successfulness in engineering, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 12: The effect of exposure to role models on students' perceptions by quartile of math performance: gender stereotypes

Outcome: Engineering to Lorena	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
Q1	0.466	-0.046	0.042	0.516	-0.046	0.042	1473	0.997
Q2	0.457	-0.001	0.042	0.508	0.054	0.037	1589	0.354
Q3	0.535	0.048	0.057	0.579	-0.019	0.074	649	0.427
Q4	0.579	0.005	0.042	0.527	0.040	0.051	941	0.588
Panel B: Main Regions								
Q1	0.464	-0.035	0.049	0.492	-0.039	0.050	1172	0.940
Q2	0.448	0.003	0.047	0.479	0.086*	0.044	1270	0.235
Q3	0.515	0.039	0.066	0.552	-0.006	0.092	520	0.644
Q4	0.589	-0.026	0.050	0.520	0.057	0.049	697	0.205

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' recommending engineering to Lorena (hypothetical female friend), separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 13: The effect of exposure to role models on students' perceptions by quartile of math performance: knowledge of engineering fields

Outcome: Types of engineering listed	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
Q1	4.348	-0.075	0.085	4.177	-0.097	0.088	1518	0.847
Q2	4.334	-0.055	0.080	4.330	0.026	0.069	1621	0.396
Q3	4.502	0.032	0.089	4.484	0.085	0.119	661	0.698
Q4	4.610	-0.096	0.070	4.526	0.040	0.088	963	0.163
Panel B: Main Regions								
Q1	4.324	-0.035	0.098	4.205	-0.142	0.094	1198	0.379
Q2	4.334	-0.004	0.085	4.346	0.030	0.077	1296	0.763
Q3	4.515	0.018	0.092	4.458	0.157	0.146	525	0.379
Q4	4.654	-0.203**	0.077	4.565	0.005	0.083	710	0.063

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' number of engineering fields listed, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table 14: The effect of exposure to role models on students' perceptions by quartile of math performance: earnings expectations

Outcome: Salary (in logarithm)	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
Q1	8.196	-0.056	0.041	8.168	-0.003	0.044	1499	0.353
Q2	8.194	-0.032	0.037	8.182	0.051	0.037	1613	0.072
Q3	8.154	-0.007	0.043	8.239	-0.087	0.054	655	0.201
Q4	8.235	-0.007	0.052	8.230	-0.056	0.043	953	0.465
Panel B: Main Regions								
Q1	8.199	-0.064	0.045	8.168	0.022	0.050	1187	0.201
Q2	8.188	0.002	0.038	8.176	0.095**	0.041	1291	0.061
Q3	8.168	-0.008	0.047	8.244	-0.090	0.068	523	0.270
Q4	8.226	0.007	0.062	8.266	-0.078	0.052	707	0.249

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' knowledge about earnings associated with engineering careers, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table 15: Students' preference for the role models' majors by quartile of math performance

Outcome: Any three types of engineering	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
Q1	0.042	-0.006	0.015	0.220	0.013	0.036	1437	0.635
Q2	0.101	0.012	0.023	0.321	0.046	0.038	1558	0.443
Q3	0.146	0.015	0.032	0.496	-0.064	0.061	646	0.225
Q4	0.142	0.104**	0.040	0.512	-0.030	0.048	939	0.019
Panel B: Main Regions								
Q1	0.034	0.000	0.016	0.202	0.051	0.038	1132	0.224
Q2	0.104	0.023	0.025	0.306	0.052	0.042	1246	0.559
Q3	0.152	0.018	0.034	0.484	-0.011	0.073	515	0.725
Q4	0.132	0.134***	0.041	0.534	-0.074	0.048	691	0.001

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for the role models' majors offered at UDEP (industrial engineering, civil engineering, or mechanical engineering), separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 16: The effect of exposure to role models on students' preference for non-stem fields by quartile of math performance

Outcome: Prefer Non-STEM	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
Q1	0.911	0.020	0.018	0.723	-0.032	0.037	1437	0.222
Q2	0.850	0.001	0.027	0.583	-0.065	0.043	1558	0.187
Q3	0.806	-0.009	0.040	0.445	0.063	0.065	646	0.319
Q4	0.795	-0.097**	0.045	0.430	-0.013	0.043	939	0.135
Panel B: Main Regions								
Q1	0.915	0.017	0.018	0.741	-0.066*	0.039	1132	0.073
Q2	0.847	-0.005	0.029	0.591	-0.051	0.049	1246	0.397
Q3	0.805	-0.023	0.043	0.462	0.000	0.070	515	0.785
Q4	0.825	-0.134***	0.046	0.416	0.020	0.045	691	0.017

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for non-STEM fields, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Online Appendix

Figures in Appendix

Tables in Appendix

Figure A1: Program evaluation timeline

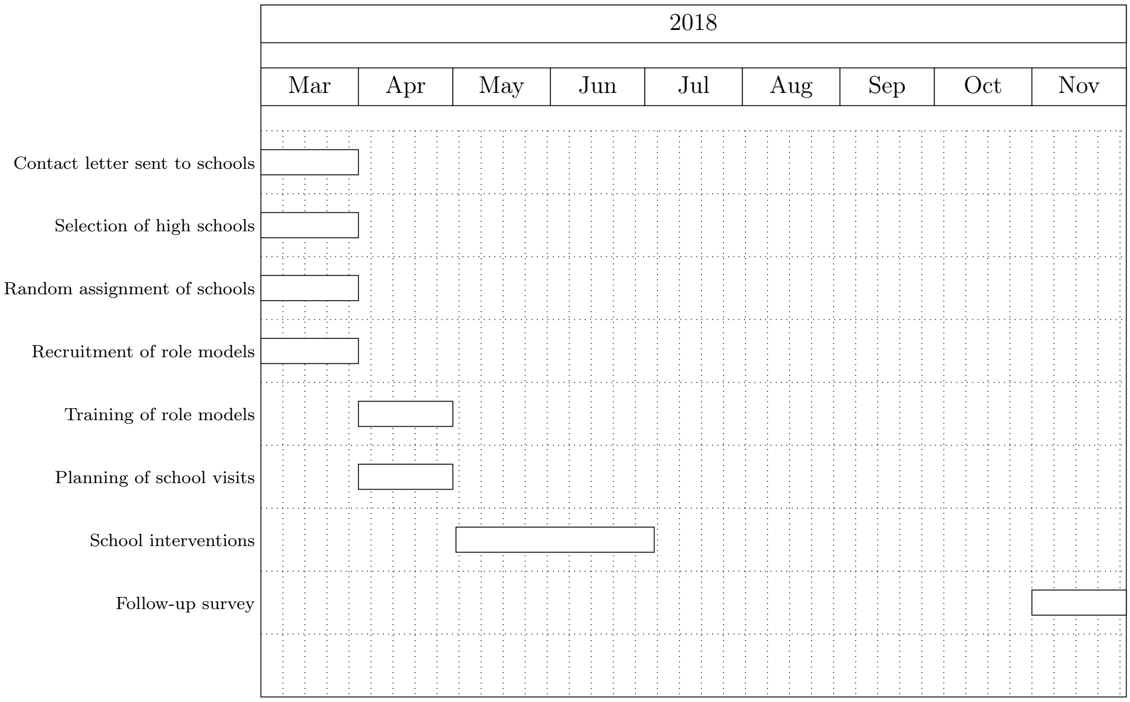
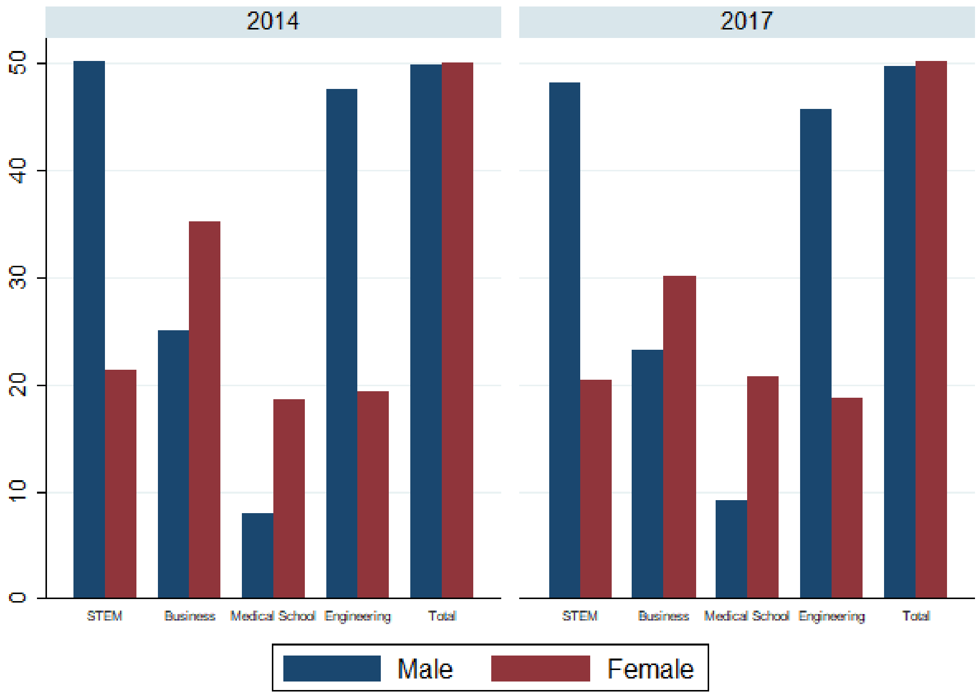


Figure A2: Thumbnails of slides shown during school visits

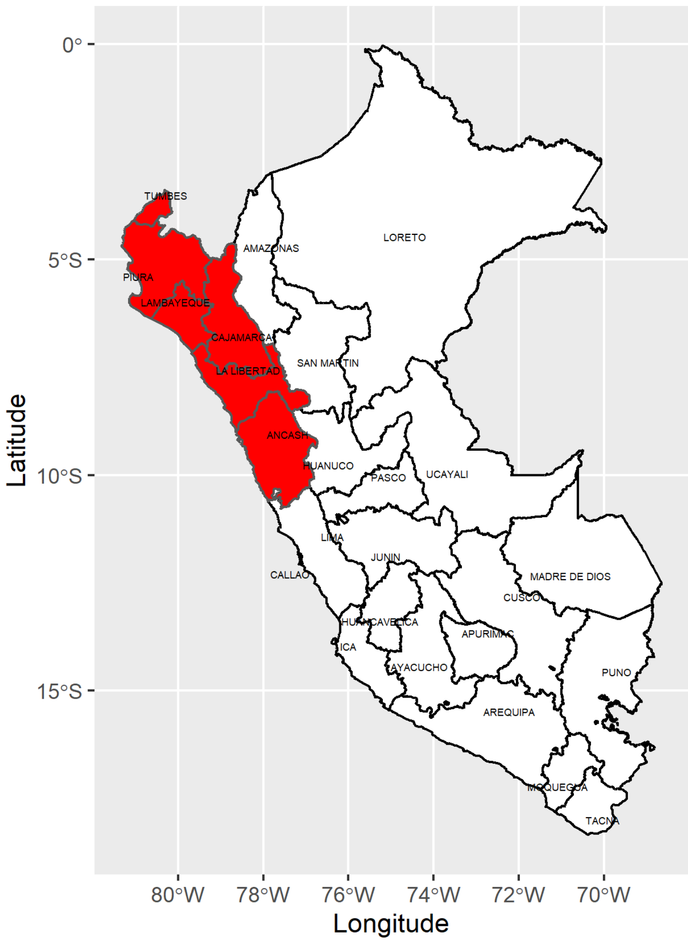
Figure A3: Thumbnails of slides shown during school visits (continued)

Figure A4: Share of male and female applicants to selective undergraduate academic programs for the whole population of applicants in 2014 and 2017, Peru



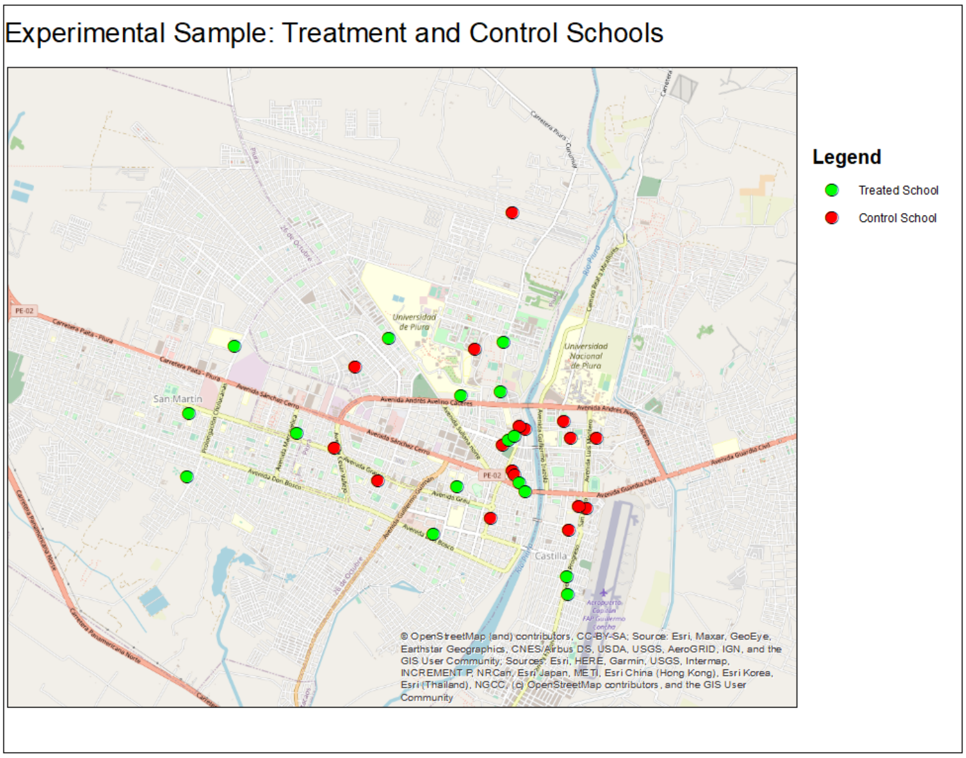
Notes: Data from public records of the Peruvian National Superintendence of Higher Education (SUNEDU): https://www.sunedu.gob.pe/sibe/.

Figure A5: Experimental sample in Peru



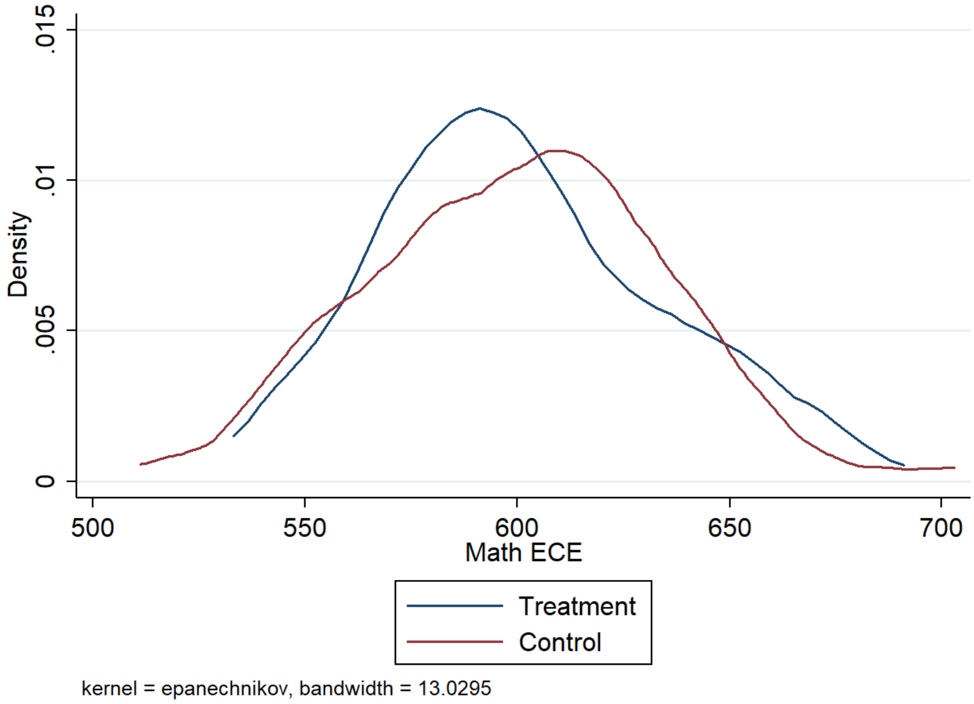
Notes: This figure shows the division of the Peruvian territory in 25 regions. The regions covered in our intervention are shaded red in the graph.

Figure A6: Experimental sample: Piura city



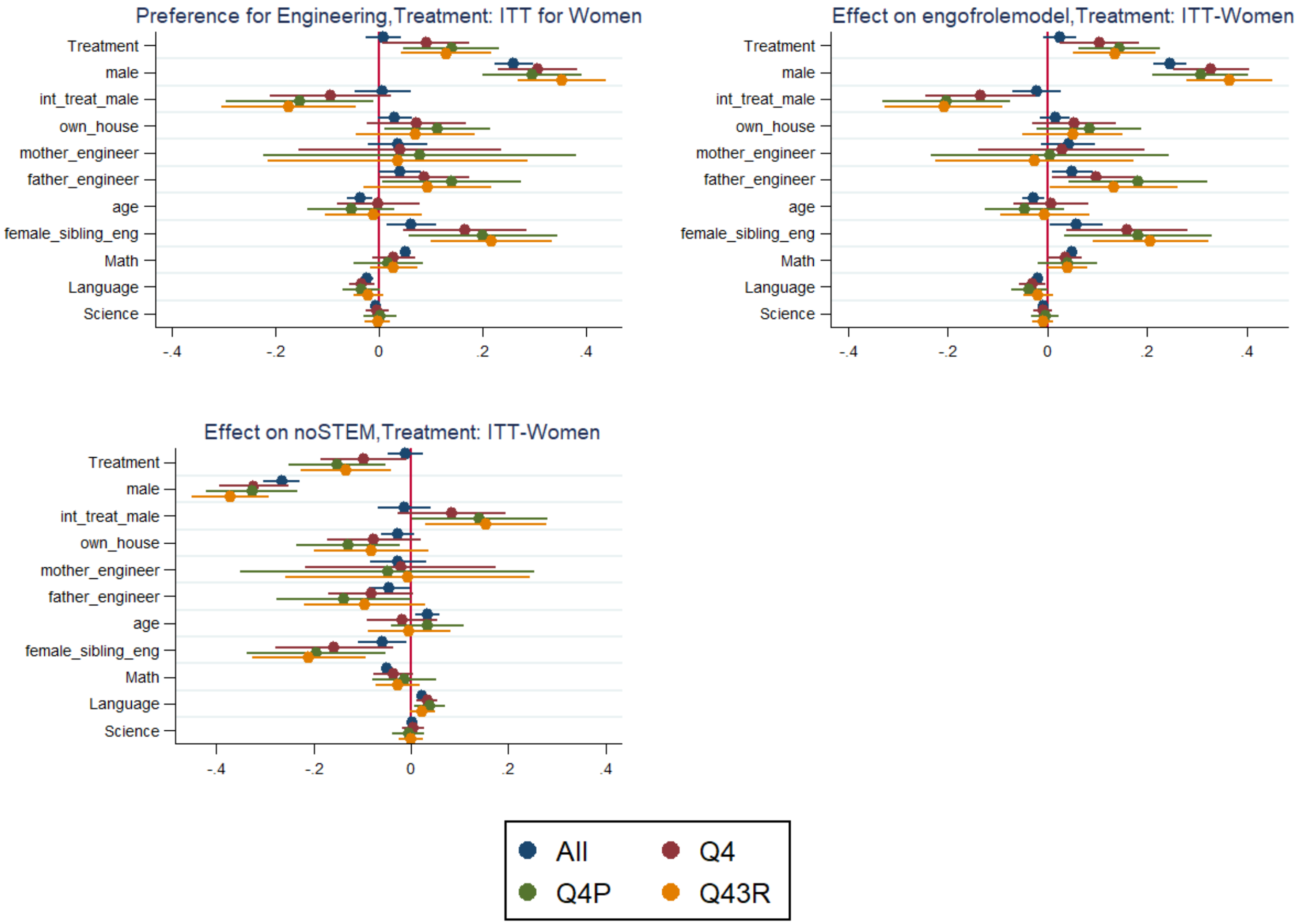
Notes: This figure shows the longitude and latitude coordinates of the schools in our sample. The sample is restricted to schools in Piura City (the role models' place of residence). The location of treatment and control schools are depicted with green and red dots, respectively.

Figure A7: Distribution of school ECE math scores



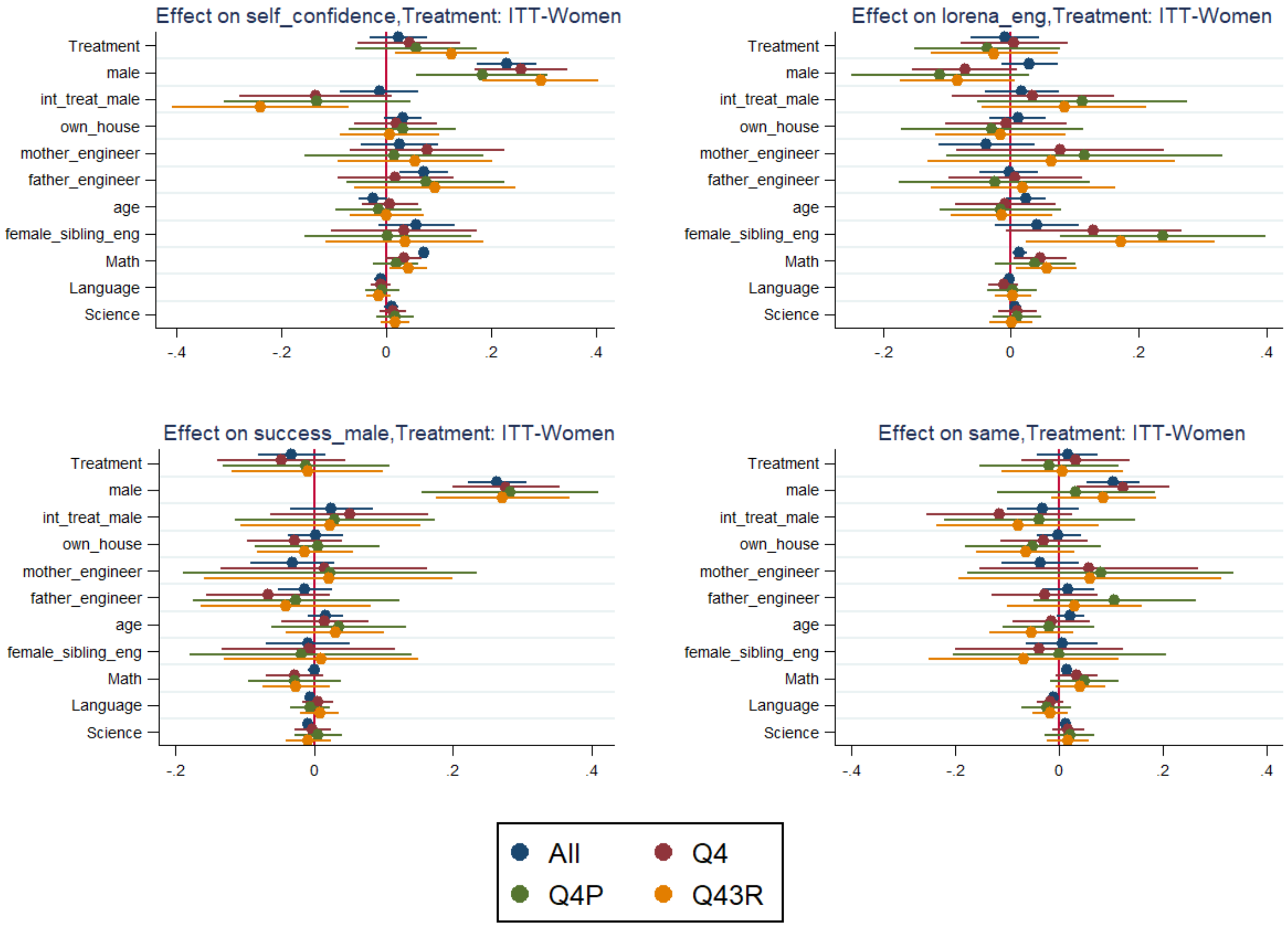
Notes: The figure shows the distribution of the math component of the ECE standardized examination of 2015 for both treatment and control schools.

Figure A8: Senior-year high school students- preference for fields of study



Notes: The figure shows the intent to treat (ITT) estimates for girls ("*Treatment*") and the effect of other covariates on senior-year students' preferences for fields of study: i) all types of Engineering, ii) the role models engineering majors (Industrial and Systems Engineering, Civil Engineering, and Mechanical/Electrical Engineering), iii) Non-STEM fields. Estimates for four subgroups are reported. *All* denotes the group for the entire sample of students, *Q4* includes only students in the upper quartile of baseline math scores, *Q4P* includes students in the upper quartile of baseline math scores and attending schools in Piura, *Q43R* incorporates students in the upper quartile of baseline math scores and attending schools in Piura, Tumbes, and Lambayeque (3 regions). Horizontal spikes denote 95% confidence intervals.

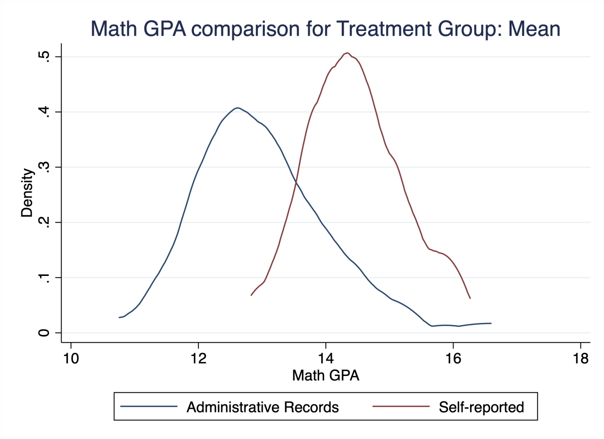
Figure A9: Senior-year high school students- perceptions



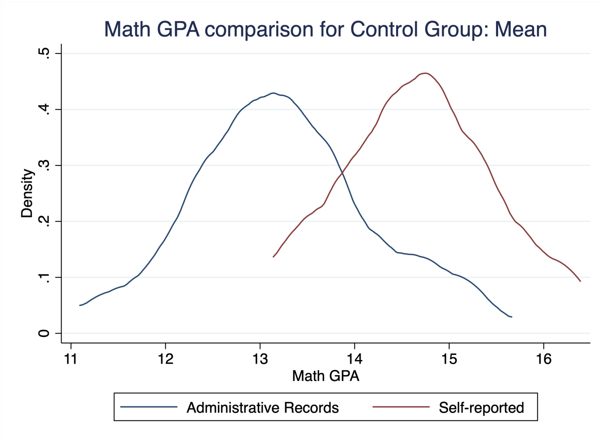
Notes: The figure shows the intent to treat (ITT) estimates for girls ("*Treatment*") and the effect of other covariates on senior-year students' perceptions: i) self-confidence in having aptitude and skills to pursue an engineering major, ii) recommending engineering to a hypothetical female friend (Lorena), iii) attributing success to men in engineering fields, iv) suggesting the same career to a hypothetical male and a hypothetical female friend. Estimates for four subgroups are reported. *All* denotes the group for the entire sample of students, *Q4* includes only students in the upper quartile of baseline math scores, *Q4P* includes students in the upper quartile of baseline math scores and attending schools in Piura, *Q43R* incorporates students in the upper quartile of baseline math scores and attending schools in Piura, Tumbes, and Lambayeque (3 regions). Horizontal spikes denote 95% confidence intervals.

Figure A10: Over-reporting by treatment status

(a) 10th Grade Math GPA- Treatment Group



(b) 10th Grade Math GPA- Control Group



Notes: The figure shows the over-reporting of math scores using i) follow-up survey and ii) SIAGIE administrative records. Panel (a) and (b) show the distribution of 10th grade school math scores for the treatment and the control group, respectively.

Table A1: Treatment-control balance

	Control Group (1)	Treatment Group (2)	Difference T-C (3)	p-value (4)
Panel A: Student level (full sample)				
Female, gender (female=1)	0.575	0.540	-0.058	0.330
Age (in years)	16.232	16.266	0.018	0.393
Math, 10th grade math GPA	14.641	14.510	-0.083	0.621
Language, 10th grade spanish GPA	15.589	15.072	-0.333	0.100
Science, 10th grade science GPA	15.201	15.042	-0.170	0.278
Years education father	13.955	13.718	-0.185	0.279
Years education mother	13.641	13.419	-0.142	0.425
Father engineer	0.151	0.146	-0.014	0.411
Mother engineer	0.032	0.038	0.003	0.682
Number of siblings	1.959	1.962	-0.006	0.908
Own a house	0.845	0.854	0.009	0.508
Mother work	0.675	0.679	0.020	0.280
Father work	0.950	0.951	0.005	0.483
Has female sibling engineer	0.044	0.041	-0.003	0.599
(*)Girls in Q4 math	0.206	0.181	-0.008	0.761
(*)Girls in Q3 math	0.139	0.155	0.012	0.638
(*)Girls in Q2 math	0.347	0.328	-0.021	0.508
(*)Girls in Q1 math	0.308	0.336	0.017	0.734
(*)Boys in Q4 math	0.225	0.186	-0.036	0.096
(*)Boys in Q3 math	0.115	0.143	0.031	0.024
(*)Boys in Q2 math	0.339	0.332	-0.022	0.277
(*)Boys in Q1 math	0.320	0.339	0.027	0.378
Number of Observations	2694	2704		
Test of joint significance excluding (*)		F-stat: 1.11 (p-value: 0.358)		
Panel B: School level (full sample)				
Average math ECE 2015	599.981	600.739	0.532	0.937
Number of teachers	14.944	16.660	1.518	0.457
Number of male teachers	7.882	9.136	1.251	0.367
Number of female teachers	7.500	8.106	0.451	0.743
Teachers-concluded pedagogy studies	23.755	27.326	3.320	0.383
Teachers-not concluded pedagogy studies	8.068	8.583	0.168	0.938
Private school	0.741	0.723	-0.051	0.555
Registration-total students	58.444	64.979	5.965	0.576
Registration-total male students	24.907	29.340	4.554	0.447
Registration-total female students	33.537	35.638	1.411	0.855
Single-sex school (only women)	0.130	0.128	-0.012	0.869
Test of joint significance		F-stat: 0.32 (p-value: 0.956)		

Notes: In panel A, the sample is restricted to students in the treatment and control groups who answered the post-treatment survey while in panel B the sample is restricted to schools in the treatment and control groups. Column 1 and column 2 report the sample mean in the control and treatment group, respectively. Column 3 displays the estimate on the treatment dummy in a regression of each variable on treatment. P-values for the statistically significance of the estimate are shown in column (4). The regression controls for city fixed effects, and standard errors are adjusted for clustering at the unit of randomization (school). A test for the joint significance of the coefficients is performed after running a regression of the treatment dummy on the baseline covariates. F-statistics are reported. Information in panel A comes from a follow-up survey implemented in 18 cities of Peru to senior-year high school students in November 2018 while in panel B the information comes from the *Censo Educativo 2017-MINEDU* and *Evaluación Censal de Estudiantes(ECE) 2015.*

Table A2: Effect on students' preference for engineering: including covariates

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Full	4Q	AM	BM	1Q	4Q3R
Treatment	0.0179	-0.00162	-0.0170	0.0416	0.0196	-0.0430
	(0.0237)	(0.0489)	(0.0367)	(0.0285)	(0.0355)	(0.0501)
Interaction	-0.00797	0.0928	0.0628	-0.0504	-0.0387	0.174***
(Treatment*female)	(0.0269)	(0.0593)	(0.0384)	(0.0328)	(0.0398)	(0.0651)
Female	-0.261***	-0.307***	-0.321***	-0.226***	-0.195***	-0.354***
gender (female=1)	(0.0184)	(0.0385)	(0.0310)	(0.0224)	(0.0251)	(0.0422)
own_house	0.0311*	0.0734	0.0571*	0.0168	-0.00729	0.0709
	(0.0164)	(0.0482)	(0.0328)	(0.0169)	(0.0260)	(0.0581)
mother_engineer	0.0364	0.0407	0.0384	0.0277	0.0227	0.0372
	(0.0290)	(0.0987)	(0.0555)	(0.0334)	(0.0456)	(0.126)
father_engineer	0.0412**	0.0876*	0.0609*	0.0239	0.00108	0.0941
	(0.0202)	(0.0442)	(0.0336)	(0.0238)	(0.0284)	(0.0623)
age	-0.0357***	-0.000528	-0.0200	-0.0422**	-0.0139	-0.00987
(in years)	(0.0124)	(0.0398)	(0.0235)	(0.0175)	(0.0196)	(0.0465)
has a female sibling engineer	0.0635**	0.167***	0.0728	0.0538	0.0370	0.218***
	(0.0246)	(0.0601)	(0.0460)	(0.0329)	(0.0423)	(0.0586)
Math	0.0510***	0.0290	0.0372**	0.0490***	0.0277***	0.0287
(10th grade math GPA)	(0.00383)	(0.0207)	(0.0147)	(0.00536)	(0.00922)	(0.0229)
Language	-0.0235***	-0.0328***	-0.0294***	-0.0206***	-0.0215***	-0.0200
(10th grade spanish GPA)	(0.00638)	(0.0120)	(0.0110)	(0.00504)	(0.00593)	(0.0143)
Science	-0.00507	-0.00310	-0.0105	-0.00350	-0.00640	-0.00208
(10th grade science GPA)	(0.00554)	(0.0114)	(0.00999)	(0.00567)	(0.00569)	(0.0122)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Parent education FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,580	939	1,585	2,995	1,437	691
Adjusted R^2	0.161	0.136	0.144	0.143	0.118	0.141

Notes: This table reports the ITT estimates of the role model interventions on grade 11 students' preferences for engineering, including the estimates on covariates. The regression controls for city fixed effects and parental education fixed effects. Standard errors are clustered at the unit of randomization (school). 4Q corresponds to the sample of students in the top 25 percentile of baseline math scores, AM for students above the 50 percentile, BM for students below median or at the 50 percentile, 1Q for students in the bottom 25 percentile, and 4Q3R includes students in the upper quartile, and who are attending schools in three main regions (Piura, Tumbes, and Lambayeque). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A3: The effect of exposure to role models on students' preference for engineering by quartile of math performance: LATE

Outcome: Prefer Engineering	Control group mean female (1)	Treatment effect (LATE) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (LATE) male (5)	Standard error (6)	N (7)	Diff (LATE) p-value (8)
Panel A: Full Sample								
Q1	0.076	-0.020	0.017	0.271	0.021	0.038	1437	0.333
Q2	0.138	0.001	0.027	0.403	0.071	0.044	1558	0.174
Q3	0.194	-0.002	0.042	0.546	-0.073	0.070	646	0.347
Q4	0.205	0.097**	0.045	0.554	-0.002	0.052	939	0.121
Panel B: Main Regions								
Q1	0.068	-0.012	0.017	0.251	0.062	0.038	1132	0.093
Q2	0.138	0.012	0.029	0.389	0.068	0.051	1246	0.329
Q3	0.195	0.012	0.045	0.527	-0.008	0.076	515	0.821
Q4	0.175	0.139***	0.046	0.573	-0.046	0.053	691	0.010

Notes: This table reports the local average treatment effects (LATE) estimates for girls and the LATE for boys on preferences for engineering, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the LATE for females and males, respectively. The estimates are obtained from a two-stage least squares (2SLS) using treatment assignment as an instrument for treatment receipt. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city and it includes covariates. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A4: Robustness check: high-ability math and science

Outcome: Prefer Engineering	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
top 25 M & S	0.184	0.090	0.069	0.506	0.005	0.092	395	0.443
top 25 M not S	0.225	0.083	0.053	0.581	-0.034	0.061	544	0.148
top 25 S not M	0.173	-0.161**	0.070	0.15	0.051	0.111	189	0.122
Panel B: Main Regions								
top 25 M & S	0.129	0.214***	0.074	0.582	-0.052	0.099	286	0.025
top 25 M not S	0.220	0.071	0.057	0.574	-0.085	0.070	405	0.091
top 25 S not M	0.211	-0.171*	0.089	0.192	0.033	0.143	135	0.278

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for engineering, separately by different groups of students based on skills in math (M) and science (S). Estimates correspond to i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A5: Robustness check: average school ECE math scores

Outcome: Prefer Engineering	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
Panel A: Full Sample								
Q1	0.076	-0.018	0.017	0.271	0.019	0.035	1434	0.356
Q2	0.138	0.018	0.026	0.403	0.078*	0.044	1539	0.219
Q3	0.194	0.013	0.042	0.546	-0.060	0.068	624	0.303
Q4	0.205	0.097**	0.041	0.554	0.018	0.047	907	0.174
Panel B: Main Regions								
Q1	0.068	-0.014	0.017	0.251	0.057	0.035	1129	0.093
Q2	0.138	0.036	0.028	0.389	0.078	0.051	1227	0.451
Q3	0.195	0.022	0.045	0.527	-0.009	0.076	493	0.711
Q4	0.175	0.132***	0.042	0.573	-0.029	0.052	659	0.016

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for engineering, separately for different subgroups of students based on self-reported baseline math scores. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (1) and it controls for average school 2015 ECE math scores. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A6: The effect on students' preference for engineering: School-UDEP distance, women in the top 25 percentile

VARIABLES	(1) Eng	(2) Eng	(3) Eng	(4) Eng	(5) Eng	(6) Eng
uddistreat	-0.142*	-0.161**	-0.156**	-0.162**	-0.167**	-0.167**
(Treatment*distanceAMUDEP)	(0.0747)	(0.0748)	(0.0745)	(0.0774)	(0.0802)	(0.0810)
distanceAMUDEP	0.119	0.109	0.109	0.192	0.181	0.181
	(0.101)	(0.115)	(0.114)	(0.120)	(0.125)	(0.125)
Treatment	0.148***	0.168***	0.162***	0.170***	0.172***	0.172***
ITT near schools	(0.0491)	(0.0481)	(0.0484)	(0.0527)	(0.0568)	(0.0570)
Treatment + uddistreat ITT far schools	0.006	0.006	0.006	0.008	0.005	0.006
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent Engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent Education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes
Observations	553	525	524	519	517	516
Adjusted R^2	0.034	0.038	0.041	0.043	0.044	0.045

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to female high ability students (fourth quartile of baseline math scores), who answered the survey. uddistreat is the interaction term between our treatment variable and a dummy variable "distanceAMUDEP" that equals one if the school distance from UDEP is above the sample median, and zero otherwise. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A7: The effect on students' preference for engineering: school-UDEP distance, men in the bottom 25 percentile

VARIABLES	(1) Eng	(2) Eng	(3) Eng	(4) Eng	(5) Eng	(6) Eng
uddistreat	-0.133**	-0.120	-0.117	-0.132*	-0.138**	-0.128*
(Treatment*distanceAMUDEP)	(0.0649)	(0.0733)	(0.0742)	(0.0714)	(0.0674)	(0.0694)
distanceAMUDEP	-0.0239	-0.0864	-0.0882	-0.0202	0.0331	0.133
	(0.0978)	(0.0873)	(0.0878)	(0.0850)	(0.0811)	(0.0857)
Treatment	0.111**	0.101*	0.101*	0.114**	0.0872*	0.0793*
ITT near schools	(0.0463)	(0.0521)	(0.0519)	(0.0481)	(0.0473)	(0.0472)
Treatment + uddistreat						
ITT far schools	-0.022	-0.019	-0.015	-0.018	-0.050	-0.049
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent Engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent Education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes
Observations	703	654	652	639	637	627

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to men in the bottom quartile of baseline math scores, who answered the survey. uddistreat is the interaction term between our treatment variable and a dummy variable "distanceAMUDEP" that equals one if the school distance from UDEP is above the sample median, and zero otherwise. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A8: The effect on students' preference for engineering: school-UDEP distance, men

VARIABLES	(1) Eng	(2) Eng	(3) Eng	(4) Eng	(5) Eng	(6) Eng
uddistreat	-0.111**	-0.115**	-0.111**	-0.101**	-0.109**	-0.101**
(Treatment*distanceAMUDEP)	(0.0466)	(0.0496)	(0.0480)	(0.0462)	(0.0497)	(0.0487)
distanceAMUDEP	-0.138**	-0.148**	-0.146**	-0.105	-0.0923	-0.0666
	(0.0630)	(0.0715)	(0.0715)	(0.0745)	(0.0612)	(0.0624)
Treatment	0.105***	0.104***	0.100***	0.0931***	0.0773**	0.0759**
ITT near schools	(0.0345)	(0.0355)	(0.0339)	(0.0310)	(0.0334)	(0.0323)
Treatment + uddistreat	-0.007	-0.011	-0.011	-0.007	-0.032	-0.025
ITT far schools						
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent Engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent Education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes
Observations	2,238	2,116	2,108	2,070	2,023	1,994
Adjusted R^2	0.012	0.012	0.013	0.020	0.080	0.081

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to men, who answered the survey. uddistreat is the interaction term between our treatment variable and a dummy variable "distanceAMUDEP" that equals one if the school distance from UDEP is above the sample median, and zero otherwise. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A9: The effect on students' preference for engineering: school-UDEP distance, women

VARIABLES	(1) Eng	(2) Eng	(3) Eng	(4) Eng	(5) Eng	(6) Eng
uddistreat	-0.0757***	-0.0734**	-0.0744***	-0.0759***	-0.0516*	-0.0419
(Treatment*distanceAMUDEP)	(0.0274)	(0.0280)	(0.0279)	(0.0278)	(0.0307)	(0.0307)
distanceAMUDEP	-0.0145	-0.0369	-0.0426	-0.00704	-0.000503	-0.00206
	(0.0491)	(0.0509)	(0.0499)	(0.0531)	(0.0590)	(0.0556)
Treatment	0.0406**	0.0385**	0.0390**	0.0394**	0.0297*	0.0266
ITT near schools	(0.0172)	(0.0176)	(0.0172)	(0.0178)	(0.0176)	(0.0175)
Treatment + uddistreat	-0.035	-0.035	-0.035	-0.037*	-0.022	-0.015
ITT far schools						
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent Engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent Education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes
Observations	2,918	2,756	2,748	2,713	2,616	2,586
Adjusted R^2	0.009	0.008	0.008	0.014	0.051	0.052

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to women, who answered the survey. uddistreat is the interaction term between our treatment variable and a dummy variable "distanceAMUDEP" that equals one if the school distance from UDEP is above the sample median, and zero otherwise. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A10: The effect on students' preference for engineering: school-UDEP distance, women (continued)

VARIABLES	(1) 4Q3R	(2) AM	(3) AM3R	(4) BM	(5) BM3R
uddistreat	-0.132	-0.0965*	-0.0785	-0.0146	0.0171
(Treatment*distanceAMUDEP)	(0.0862)	(0.0520)	(0.0557)	(0.0297)	(0.0416)
distanceAMUDEP	-0.920***	0.247**	-0.510***	-0.0720	-0.182***
	(0.0922)	(0.0958)	(0.0411)	(0.0634)	(0.0157)
Treatment	0.173***	0.0904***	0.0925***	-0.00343	-0.00375
ITT near schools	(0.0545)	(0.0324)	(0.0325)	(0.0136)	(0.0141)
Treatment + uddistreat	0.041	-0.006	0.014	-0.018	0.013
ITT far schools					
Observations	387	896	701	1,690	1,390
Adjusted R^2	0.051	0.039	0.041	0.029	0.038

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to female students, who answered the survey. uddistreat is the interaction term between our treatment variable and a dummy variable "distanceAMUDEP" that equals one if the school distance from UDEP is above the sample median, and zero otherwise. "4Q3R" stands for upper quartile of baseline math scores in three main regions, "AM" stands for baseline math scores above the median, "AM3R" includes individuals with baseline math scores above the median and in three main regions, "BM" stands for baseline math scores below median, and "BM3R" denotes below median of baseline math scores in three main regions. Covariates include baseline scores in 10th grade, student's age in years, mother or father engineer indicator, ownership of house, parental education fixed effects, and an indicator for having a sibling engineer. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A11: The effect on students' preference for engineering: school-UDEP distance, men (continued)

VARIABLES	(1) 1Q3R	(2) AM	(3) AM3R	(4) BM	(5) BM3R
uddistreat	-0.0479	-0.0949	-0.131	-0.0894	-0.113*
(Treatment*distanceAMUDEP)	(0.0664)	(0.0713)	(0.0933)	(0.0591)	(0.0659)
distanceAMUDEP	0.430***	-0.149**	-0.165***	0.0333	-0.0648**
	(0.0985)	(0.0627)	(0.0427)	(0.0998)	(0.0253)
Treatment	0.0784	0.0390	0.0383	0.0880**	0.0880**
ITT near schools	(0.0474)	(0.0469)	(0.0487)	(0.0439)	(0.0438)
Treatment + uddistreat	0.030	-0.056	-0.092	-0.001	-0.025
ITT far schools					
Observations	473	689	505	1,305	988
Adjusted R^2	0.046	0.011	0.007	0.075	0.073

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to male students, who answered the survey. uddistreat is the interaction term between our treatment variable and a dummy variable "distanceAMUDEP" that equals one if the school distance from UDEP is above the sample median, and zero otherwise. "1Q3R" stands for first quartile of baseline math scores in three main regions, "AM" stands for baseline math scores above the median, "AM3R" includes individuals with baseline math scores above the median and in three main regions, "BM" stands for baseline math scores below median, and "BM3R" denotes below median of baseline math scores in three main regions. Covariates include baseline scores in 10th grade, student's age in years, mother or father engineer indicator, ownership of house, parental education fixed effects, and an indicator for having a sibling engineer. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A12: Heterogeneous effects by type of engineering: only girls

	Preference for Engineering: Girls					
	Treatment effect (ITT)					
	Full Sample (1)	Above median (2)	4th Quartile (3)	Above median 3R (4)	4th Quartile 3R (5)	4th Quartile No 3R (6)
Industrial Engineering and Systems	0.015	0.032*	0.021	0.049***	0.040	-0.032
	(0.010)	(0.018)	(0.026)	(0.018)	(0.025)	(0.061)
Civil Engineering	0.009	0.026*	0.052***	0.022	0.063***	0.021
	(0.007)	(0.015)	(0.019)	(0.018)	(0.021)	(0.038)
Electrical and Mechanical Engineering	0.003	0.008	0.012	0.008	0.009	0.019
	(0.003)	(0.008)	(0.013)	(0.010)	(0.017)	(0.015)
N	2918	974	553	757	414	139

Notes: This table reports the treatment effects estimates on girls' preferences for Engineering by major, for different groups of students.The data is from a post-visit survey. Students' academic performance in math is measured by the students' score on math the previous year corresponding to grade 10. Intent-to-Treat estimates are displayed. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A13: Balance Test: Inflation of Math GPA

	Control Group (1)	Treatment Group (2)	Difference T-C (3)	p-value (4)
Over-reporting math grades	1.402	1.433	0.031	0.784
Over-reporting math grades for girls	1.225	1.285	0.060	0.626
Over-reporting math grades for boys	1.587	1.558	-0.029	0.845

Notes: This table shows the average school inflation of 10th math GPA in our follow-up sample. Column 1 and column 2 report the sample mean in the control and treatment group, respectively. Column 3 displays the estimate on the treatment dummy in a regression of each variable on treatment. P-values for the statistically significance of the estimate are shown in column (4). Information comes from a follow-up survey implemented in 18 cities of Peru to senior-year high school students in November 2018 and from administrative records of SIAGIE 2017- MINEDU.

Survey Instruments

Student survey: survey about preferences and perceptions of fields of study among senior-year high school students in Peru

Q1. School:
Q2. City:
Q3. Sex: 1. ☐ male 2. ☐ female
Q4. Age (In years completed):
Q5. Final course grade on Math in grade 10:
Q6. Final course grade on Language in grade 10:
Q7. Final course grade on Science in grade 10:
☺ If you do not remember exact grades please write an approximation.
☺ Now, we are going to ask easy questions about your career preferences. Remember that there is no correct or incorrect answer. Please respond to the following questions honestly.
Q8. Would you like to study at university after graduating from high school? (Important: select only one option. If you are still undecided, select the option that comes close to what you would like to do)
1. ☐ Yes ⟶ (Go to question Q9 and continue the survey if your choice was "Yes")
2. ☐ No ⟶ (Go to question Q10 and continue the survey if your choice was "No")

Q9. Please write the name of the career you would like to study the most in any university. (If you are in doubt between several careers that you like the same please write the name of one of them)
Q10. Have you already decided at which university to study? (Select the option that applies)
1. ☐ Yes ⟶ (Go to question Q11 and continue the survey if your choice was "Yes")
2. ☐ No ⟶ (Go to question Q12 and continue the survey if your choice was "No")

Q11. Please answer questions Q11a, Q11b, and Q11c:
Q11a. Write the name of the university where you have decided to study:
Q11b. Write the name of the career that you are going to study at this university:
Q11c. Are you already enrolled or have you reserved a place in this university? (Select one option only and go to question Q12. Continue the survey)
1. ☐ Yes 2. ☐ No
☺ Read carefully each of the following questions, and answer according to your own view. Remember that there is no correct or incorrect answer.
Q12. Imagine that Javier and Lorena are two of your best friends. Both of them have a final course grade in Math and in Science of 20. Javier and Lorena are

not sure which career to study. Which field of study would you suggest to each of them?
Field of study that you suggest to Lorena:
Field of study that you suggest to Javier:
Q13. One person studied Informatics Engineering in the best university in Peru. After having worked for more than 10 years in companies such as Microsoft, Facebook, IBM, and Google, this person started his/her own business. His/her company is one of the top five leading engineering companies in the country. In your opinion: (Please select one option only)
1. ☐ Even though this person can be male or female, it is more probable that is male.
2. ☐ Even though this person can be male or female, it is more probable that is female.
Q14. One type of engineering is civil engineering. Please list five other types of engineering: (If you do not remember another five types of Engineering, list the ones you remember and leave the other blanks unfilled)
Q15. One person graduated from the Industrial Engineering program offered by a university in Peru two years ago. Currently, the person is working. How much do you think the person earns per month? (Select one option only)
1. ☐ Less than 1000 soles 3. ☐ Between 2000 and 3000 soles 5. ☐ Between 4000 and 5000 soles
2. ☐ Between 1000 and 2000 soles 4. ☐ Between 3000 and 4000 soles 6. ☐ Between 5000 and 6000 soles
7. ☐ Between 6000 and 7000 soles 8. ☐ Between 7000 and 8000 soles 9. ☐ Between 8000 and 9000 soles
10. ☐ More than 9000 soles
Q16. Do you think you have the capacities and qualities to study Engineering at university? (Select one option only)
1. ☐ Yes, I have them 2. ☐ No, I don't have them 3. ☐ I don't know
☺ Next, we are going to ask you some easy questions about your parents. Please respond the best you can to the following questions:
Q17. Age of your father/ attorney in years completed:
Q18. Is your father/attorney an engineer? (Select the option that applies): 1. ☐ Yes 2. ☐ No
Q19. Please select the level of education of your father/attorney:
1. ☐ Primary education completed 3. ☐ Technical education incomplete 5. ☐ University incomplete

2. ☐ Secondary education completed 4. ☐ Technical education completed 6. ☐ University completed

Q20. Does your father/ attorney work?: 1. ☐ Yes 2. ☐ No

Q21. Age of your mother in years completed:

Q22. Is your mother an engineer? (Select the option that applies): 1. ☐ Yes 2. ☐ No

Q23. Please select the level of education of your mother:

1. ☐ Primary education completed 3. ☐ Technical education incomplete 5. ☐ University incomplete

2. ☐ Secondary education completed 4. ☐ Technical education completed 6. ☐ University completed

Q24. Does your mother work?: 1. ☐ Yes 2. ☐ No

☺ Now we are going to ask questions about your siblings. For each question cross the cell that corresponds:

Q25. How many siblings do you have in total? $\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q26. How many brothers do you have in total? $\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q27. How many sisters do you have in total? $\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q28. How many of your brothers are currently studying at university?
$\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q29. How many of your sisters are currently studying at university? $\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q30. How many of your brothers are currently studying engineering?
$\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q31. How many of your sisters are currently studying engineering?
$\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q32. How many of your brothers are engineers?
$\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q33. How many of your sisters are engineers?
$\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

☺ Now, we are going to ask some easy questions about the household. Please answer them the best you can:

Q34. Does your family live in an own or rented house?: 1. ☐ Own 2. ☐ Rented 3. ☐ Other (Specify):

Q35. Is there a car or truck in your home? :

1. ☐ Yes → How many? $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{\geq 5}$

2. ☐ No

Q36. Is there a motorcycle in your home? :

1. ☐ Yes → How many? $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{\geq 5}$

2. ☐ No

Q37. Is there a TV in your home? :

1. ☐ Yes → How many? $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{\geq 5}$

2. ☐ No

Q38. Is there a computer or laptop in your home? :

1. ☐ Yes → How many? $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{\geq 5}$

2. ☐ No

Q39. Do you have internet access at home? : 1. ☐ Yes 2. ☐ No

Q40. Have you gone on vacation with your family to any place in Peru this 2018? : 1. ☐ Yes 2. ☐ No

Q41. Have you traveled abroad with your family this 2018? : 1. ☐ Yes 2. ☐ No

☺ Finally, tell us whether did you register to take the University of Piura's PAE test in 2018, and to what career did you apply in the PAE:

Q42. Did you register to take the University of Piura's PAE test this year 2018? (Select the option that applies) :

1. ☐ Yes (If "Yes" go to question Q43)

2. ☐ No (If "No", this is the end of the survey, thank you!)

Q43. To what career did you apply in the PAE test? (Please state the career that you selected when you registered to take the PAE test) :

Thank you!