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Women in Engineering: The Role of Role Models*

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Abstract

Gender disparities in STEM fields participation are a major cause of concern for policymakers around the world. In addition to talent misallocation, low female enrollment rates in STEM careers contribute to gender-based inequalities in earnings and wealth, given the higher average level of earnings in these fields. This paper studies the effects of exposure to role models on female preferences for STEM majors. We conduct a randomized control trial where female senior students currently enrolled in engineering programs at an elite private university in Peru give talks about their experiences at randomly selected high schools. We find that exposure to this treatment increases high ability female students' preferences for engineering programs by 14 percentage points. The effect is only statistically significant for the subgroup of female students with baseline math scores in the top 25 percentile, and who reside close to the city where the role models' university is located. We also find positive but smaller effects on "low ability" male students. In a context where females are discouraged from enrolling in STEM fields, our results have important policy implications.

Keywords: Enrollment gender gap, field experiment, role models, Higher Education, career choices, stereotypes

JEL classification codes: C93, I23, I24, J16

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1 Introduction

Despite significant progress in college education access for women in recent decades, there is still a gender enrollment gap in STEM majors. Within STEM disciplines, the participation of women in engineering, one of the main STEM fields, remains significantly below that of males in not only developing countries but also developed ones. While in the 2017-18 academic year 57% of bachelor's degrees were conferred to women in the United States; only 13% of bachelor's degrees in engineering were awarded to females.¹ A recent report by UNESCO (2017) shows that in Latin America 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 the society in general. It contributes to the under-representation of females at the top of the income distribution,² it has negative effects towards the development of new ideas, science, technology and firms productivity, and critical repercussions on economic growth via the misallocation of talent.³

The persistence of gendered paths in career choices reinforces the prevalence of negative stereotypes and beliefs about women fit for STEM fields. Women are believed not to be good at math, and therefore better suited for careers in the humanities or the social sciences. On the other side, men are expected to be naturally good at math and to excel at engineering majors. This further demotivates women to choose careers accordingly to their actual talent and abilities.⁴ Under the assumption of no gender differences in innate abilities and conditional on cognitive abilities, gender imbalances in engineering lead to misallocation of resources, as individuals may not be choosing careers in which they have a comparative advantage. Due to the inefficient allocation of talent, aggregate output could be significantly affected.

Understanding the causes of low female participation in STEM fields is a relevant research and policy question, which has been studied by professionals in various fields. Several factors have been proposed as determinants of the observed gender gap in STEM, 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

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

²Brown & Corcoran (1997), Blau & Kahn (2017), Ortiz-Ospina & Roser (2018)

³Weinberger (1999), Bear & Woolley (2011), Hoogendoorn et al. (2013), Ellison & Mullin (2014), Bayer & Rouse (2016), Hsieh et al. (2019)

⁴Gender diversity in the STEM sector is important as it leads to the reduction of wage disparities between women and men, and it increases the quality of work and innovation, attainable under a more diverse environment. Engineering, for instance, is the highest-earning major in STEM in Peru, and it generates similar earnings than business majors. According to the Employment and Education Observatory of Peru, an initiative of the Ministry of Labour and Employment Promotion and the Ministry of Education with the collaboration of the Peruvian Institute for Business Alliance (IPAE), Telecommunications Engineering is the engineering major with the highest average monthly income (about 980 US\$) for the period 2013-2017, followed by Electrical Engineering (940 US\$), and Industrial Engineering (890 US\$). Similarly, Agribusiness (1118 US\$), Health and Medicine (1001 US\$), Business Administration (955 US\$), and Economics (901 US\$) are among the top-paying majors. On the other hand, Education and Mathematics are considered low-paid careers with an average monthly income of US\$420 and US\$433, respectively.

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 are looking at non-cognitive abilities (i.e. self-efficacy, self-perception) as potential drivers of the lack of women in STEM [Correll (2001), Kahn & Ginther (2017)]. Within STEM fields, the evidence strongly suggests that engineering has a low proportion of females due to women’s perception that engineering is a career not suitable for them. 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, as they lack the necessary math skills as well as due to the discrimination faced by women within STEM fields in the labor market [Emerson et al. (2012)].⁵

This paper addresses an important, yet under-studied factor which may play a key role at explaining the gender gap in STEM careers: female role models. Growing up, most of us have had that one person(s) we have looked up to, inspired us, and hoped to emulate. However several barriers restrict young girls access to female role models in STEM, such as their relative scarcity in several contexts, as well as the absence of educational policies that bring the experience of the few ones to young girls. It is therefore difficult for high school girls to come into direct contact with women who have majored or are majoring in male-dominated STEM fields, such as engineering. Our intervention aims to help alleviating this problem and brings those scarce role models close to high school girls.⁶ We collaborated with a private elite university in Northern Peru, in the context of a randomized controlled trial, and provided role model talks to 11th graders. Our role models were female senior students or very recent graduates in engineering. We then evaluate the impact of our role models intervention on high school girls preferences towards STEM majors, in particular engineering ones.

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.⁷ However, most studies suffer from identification issues related to the unobserved preferences of instructors towards same gender students, 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, the mechanism of causality cannot be clearly delineated. Our paper isolates the role model channel through random, exogenous, variation in role model exposure, although it focuses on female role models who are not instructors.⁸

⁵Some authors point out the competitive nature in STEM fields as a reason for the low participation of women in Science and Engineering [Gneezy et al. (2003), Niederle & Vesterlund (2007), Niederle & Vesterlund (2010), Buser et al. (2014), Flory et al. (2014), Reuben et al. (2017)].

⁶Even though it would be interesting to randomize the gender of the role model students were exposed to, by including male role models as well, previous interventions have shown that only female role models can impact the aspirations and gender attitudes of both male and female students [Kipchumba et al. (2021), Lim & Meer (2020)].

⁷Canes & Rosen (1995), Rothstein (1995), Neumark & Gardecki (1998), Bettinger & Long (2005), Dee (2007), Hoffmann & Philip (2009) Carrell et al. (2010), Bottia et al. (2015), Eble & Hu (2017), Lim & Meer (2017), Kofoed & McGovney (2019), Lim & Meer (2019)

⁸Other studies have also analyzed the effects of non-teaching role model interventions in the field [Nguyen (2008), Beaman et al. (2012), Del Carpio & Guadalupe (2018), Ashraf et al. (2020), Porter & Serra (2020), Breda et al. (2020)].

More closely related to our paper is a recent study by Porter & Serra (2020). They assess the effect of simultaneous exposure to two female role models, who are professionals economists, on freshman students' decision to major in Economics. Each role model visit consisted of a 15-minute discussion about the role model's experiences as an economics major, career paths, and achievements. The authors show that a brief exposure to a female role model increases students' academic performance and it influences major choices. In our study, we also investigate the effect of a brief role model exposure, but a bit earlier in life: during the last year of high school. Also importantly, while Porter & Serra (2020) focus on economics as a major choice, we focus on a STEM field in which females have a lower degree of participation: engineering. Another experimental study also related to ours is the one by Breda et al. (2020). In this study, female middle age 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. Different from these previous studies, the role models in our intervention are senior students or very recent graduates in engineering, and therefore younger and closer in age to the objective public. Therefore, we expect our role models not only to motivate high school students but also high school students to feel more connected and closer to them. Moreover, their time availability and schedule is likely more flexible than that of middle or advanced career female role models.

Our paper relates to three strands of the literature. Firstly, it adds to the extensive body of research on the causes of the gender gap in STEM, particularly 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 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. Secondly, the paper contributes to studies in social psychology that look at the effect of gender stereotypes on women's under-representation in science [Diekmann & M. Steinberg (2013)]. Several studies in social psychology have analyzed mentoring programs and non-teaching role model interventions [S. Cheryan et al. (2013), Macphie et al. (2013)], but have not been successful at tracking the causal effects on career choices and isolating the related mechanisms. This paper fills this gap as well. Thirdly, 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),⁹ our intervention relies on direct communication between role models and our target population.

In contrast with previous role model studies, we run a field experiment using a face to face communication between female senior students or recent graduates in engineering fields from an elite private university: Universidad de Piura (UDEP),¹⁰ and senior-year high school students in Northern Peru. We test whether exposure to female senior students/recent graduates in engineering acting as role mod-

⁹Ferrara et al. (2012), Riley (2017), Bernard et al. (2014)

¹⁰UDEP is a private university in Peru. It ranks among the nine top universities in Peru according to the QS Latin American University Rankings 2020.

els can change high school girls' engineering perceptions, self-confidence and ultimately increase the proportion of girls preferring engineering majors at college. Our main dependent variable is a binary indicator equal to one if the high school student plans to enroll in engineering at any higher education institution in the country and zero otherwise. It was constructed from the students' responses to a follow-up survey administered six months after the role model visits in both treatment and control schools. The intervention took place during the academic year 2018 in 51 randomly selected high schools located in Northern Peru, while another 58 schools form our control group. Our total sample roughly contains 5000 students in 11th grade, which is the final year of secondary education in Peru, a period when most high school students start looking for higher education opportunities.¹¹

An key advantage of our intervention is that the role models are senior engineering students or recent engineering graduates with first-hand experience and knowledge on the skills, aptitude and motivation needed to pursue and successfully navigate the engineering studies at college. The role models¹² have rarely interacted with the target population, they volunteered to be role models, and were trained before giving a speech to audiences made of male and female high school students.¹³ The task of the role models was to give 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 physical different", "women are very creative and they can contribute to new ideas", "To study Engineering creativity, effort, and desire to change the World are also very important".

While some researchers suggest to focus the attention on training programs offered to early age students, between 5-10 years old [Signorella et al. (1993)], in order to achieve stronger effects on students' career choices and significantly influence gender stereotypes, we believe that interventions that target senior high school students, particularly females, are also a relevant and necessary. Firstly, making a career choice is an important decision in life, therefore, it requires sufficient knowledge and awareness that a child of 5-10 years might not have. Moreover, in contexts like the Peruvian one, females are likely to be heavily exposed to gender stereotypes through all their school years. Secondly, the Peruvian educational system does not have a specific science track that segregates students within schools based on skills and preferences from a relatively early age. In fact, all students must follow the same curriculum. Under this context, a low-cost intervention that exposes senior-year high school students to female role models may influence the career choices of students at the margin and could change

¹¹We choose to focus on engineering as it is the main STEM field in Peru, and it is predominantly male-dominated. According to the National Superintendence of Higher Education in Peru (SUNEDU), only 25% of students enrolled in engineering are women.

¹²For the purpose of the intervention, we worked with 12 engineering students who acted as role models.

¹³It was not possible to give the speech to only female students because of high schools' institutional policies. In addition, we were also interested to measure the role model intervention on senior-year male high school students' choices. One of the key messages of the talk was that you do not need to be a mathematical genius to succeed in engineering, and that imagination and creativity are also relevant. Hence, the intervention might have also encouraged medium or low math-ability boys to pursue engineering fields.

students' perceptions.

The results from our random control trial (RCT) and related follow-up survey suggest that exposure to a female role model can increase female high school students' preferences towards engineering. Our evidence also suggests that this effect is particularly strong among high math ability girls, particularly those attending high schools located geographically close to the role models university.¹⁴ Being in a school that has received the role model visits increased 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.¹⁵ This corresponds to a more than 77% increase in preferences for engineering in treatment schools compared to the control ones.¹⁶ The size of our treatment effects are similar to Breda et al. (2020), who find that a sensitization program monitored by female role models encouraged female students in the 80th percentile on the Baccalauréat math test to enroll in a selective STEM program in France by 16.3 percentage points.

To shed light on the possible mechanisms underlying our main results, in the follow-up survey administered six months after the role models intervention we asked a series of questions on perceptions and self-confidence related to engineering studies. We primarily find that the treatment significantly increased female students' self-confidence to perform well in engineering and reduced female students' uncertainty about their own abilities. In general terms, our study confirms the relevance of role models to help reducing the STEM gender gap, and presents a low-cost intervention that can be easily adapted and implemented to promote STEM majors in contexts similar to the Peruvian one.

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 establishes policy recommendations.

¹⁴The presence of regional effects in role model interventions has already being pointed out by previous studies in the literature. Hardt et al. (2020) for example studies the effect of online mentoring programs at a large public German university to improve online teaching effectiveness during COVID-19. The mentees in this study were undergraduate students enrolled in the second term, and mentors were students in a more advanced terms but enrolled in the same study program as the mentees. The authors find that students, who reside in the region where the university is located, benefit more from the program. The mentoring program had positive effects on students' motivation, exam registrations, and academic performance, and the effects were stronger for male students.

¹⁵When we restrict the analysis to schools in Piura, Tumbes, and Lambayeque, we find a statistically significant increase in preferences for engineering majors of 13 pp (at 1% level) as reported by girls (in the upper quartile of math scores) in treatment schools. Significant estimates but lower in size are found for girls (above median math scores) in the same regions. (7 pp)

¹⁶We 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 university.

2 Institutional Context and Experimental Setting

In 2018 we implemented a field experiment that randomly assigned 51 high schools located in Northern Peru to a treatment that consisted in female role models visits which promoted engineering studies. 58 others schools were assigned to the control group. A follow-up survey was implemented to collect students information on career preferences and perceptions in all schools in our RCT sample (treated and control) approximately six months after the intervention. In this section, we will describe the educational setting and general context where the experiment took place. Also, we will explain in detail our role models intervention.

2.1 High School Setting and STEM Female Under-representation in Peru

In Peru, education is compulsory from the age of 5 to the age of 16, with the school year running from March to December, as Peru is located in the Southern Hemisphere. The school system consists of six years of elementary education and five years of secondary education. Approximately 2.5 million students are enrolled at the high school level,¹⁷ and 15000 high schools are active across the 25 country regions.¹⁸ At the high school level, classes are usually administered by different instructors depending on the subject.¹⁹ Some schools have morning schedules while others have afternoon schedules or both. While public schools are free, there are also private schools. All students in both private and public schools are required to cover the same curriculum during primary and secondary education, which is set by the Ministry of Education. The curriculum does not distinguish between students who aim to pursue STEM²⁰ and non-STEM college careers later in college. Furthermore, Peru does not have a centralized admission test for those students who want to continue higher education, 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 private universities other admission mechanisms are also present. For example, some offer direct admission to students in the upper third of their classroom GPA distribution.

The schools in our intervention sample are located in 6 out of 25 regions, and all of them are located in the north of the country. Roughly 60% of the schools (64 schools) are in the Piura Region, where UDEP main campus (established in 1969) is located. 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

¹⁷76% of students are enrolled in a public school, and 90% of students are registered in schools located in urban areas. (2017 Census of Schools, MINEDU)

¹⁸The Peruvian territory is divided into three administrative units: i) regions, ii) provinces, and districts (municipalities). Regions and districts are the largest and smallest administrative units in Peru, respectively. There are in total 1834 districts across the Peruvian territory.

¹⁹Subjects that form part of the National Curriculum are Mathematics, Communication, Foreign Language, Art, History, Geography, Economics, Civic, Social Skills, Physical Education, Religious Education, Science, Technology, and Environmental Studies.

²⁰STEM includes Biology, Chemistry, Maths, Statistics, Engineering, or Physics; however, in Peru Engineering is the most popular STEM field.

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. 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, over the period 2016-2017 only 30% (1 out of 3) of those applying for admission into a STEM field²¹ were women.²² Moreover, over the same period only 19% of female applicants all around the country selected engineering fields as their major of study; whereas 46% of male applicants chose engineering majors during the admission process.

2.2 Universidad de Piura

Universidad de Piura (UDEP) is a Peruvian non for profit private university located in the city of Piura, in the northern coast of Peru. Established in 1969, 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.²³ 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 it has also consistently attracted students from the neighbouring regions of Lambayeque (to the south) and Tumbes (to the north). Students from these three regions compose about 95% of UDEP Piura campus student population. In this sense, UDEP prestige and reputation as a regional university mainly concentrates in the region of Piura and the neighbouring regions of Tumbes and Lambayeque.

In general, high school students application patterns at UDEP resemble those observed at the country level. According to the university administrative data, only 20% of all women applicants at UDEP selected engineering during the period 2016-2017. Moreover, 65% of engineering applicants were male, while 35% were female.

Figure 1 depicts the number of students enrolled in engineering at UDEP over the past 10 years. While there is clearly an upward trend in engineering enrollment, the enrollment gender gap remains steady, both for all cohorts and for first-semester students only (see Figure 2). With respect to gender disparities, note that only 30% of students enrolled in engineering at UDEP are women. The ratio of the percentage of men enrolled in engineering to the percentage of women enrolled in the same major is 2.36 (2009-2018 average), meaning there are more than two men for every woman enrolled in engineering at the university. As we mentioned before, this numbers closely resemble what we observe at the country level.

²¹Science, Biology, Mathematics, Statistics, Engineering, Physics, and Chemistry. Medical undergraduate studies are not considered STEM in the statistics. In medical undergraduate studies women are over-represented (70% are women).

²²Administrative records of the Peruvian National Superintendence of Higher Education (SUNEDU):<https://www.sunedu.gob.pe/sibe/>

²³Civil Engineering, Industrial and System Engineering, and Mechanical and Electrical Engineering.

2.3 The Field Experiment

Our experiment started in 2018 (see Figure 3), and it was targeted at female and male senior-year high school students in six Northern Peruvian regions. The school-based interventions consisted on role model talks carried out by senior female engineering students or recent college graduates in Engineering from UDEP in the months of May, June and July.

Content of the interventions. The role models talks lasted 20-minutes and during their presentations they use a set of slides highlighting the following facts:²⁴ (i) the differences in brain structure among males and females, (ii) the contribution of female engineers in the creation of things throughout the introduction of successful women in engineering, (iii) definition of engineering as a channel to change the World and to make it better, and as the art of solving problems, (iv) statements aimed at deconstructing stereotypical views about engineering under the title “Beliefs or Reality?”,²⁵ (v) the experience of the role models at UDEP, and (vi) the capability of girls to become engineers. During and after their presentations, they answered questions from students.

Experiment Design. The experiment was carried out in 18 cities of Peru.²⁶ Together the 18 cities have 225,000 high school students equally gender-balanced (50% women, 50% men) in 880 high schools, which represents 33% of the high school student population in Northern Peru;²⁷ and 9% of the total high school enrollment in Peru.²⁸

Our team got access to a list of 150 schools provided by UDEP, in which our intervention could take place. These schools have been frequently visited by UDEP school admission officials in the last five years to promote UDEP majors and admission mechanisms. The 150 schools represent approximately 17% of the high schools operating in the 18 cities. Of these schools, 109 schools were finally chosen to conform our sample.²⁹ The overall experimental sample includes roughly 5378 students, and it represents 12% of the population of 11th graders in Northern Peru.³⁰

Randomization. The randomization was stratified at the city level. The schools selected by our team were subject to random assignment within each city, half of the schools in each city- or half rounded up or down to the nearest integer where there was an odd number of schools- are classified in the

²⁴Thumbnails of the slides shown during the school intervention are displayed in the Appendix.

²⁵In 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

²⁶Cajamarca, Catacaos, Chiclayo, Chimbote, Chota, Chulucanas, Cutervo, La Union, Pacasmayo, Paita, Piura, Sechura, Sullana, Talara, Tambogrande, Trujillo, Tumbes, and Zarumilla

²⁷Piura, Cajamarca, La Libertad, Lambayaque, Ancash, Tumbes

²⁸See ESCALE Statistics based on the 2019 School Census Data administered by the Peruvian Ministry of Education: <http://escale.minedu.gob.pe/padron-de-ieee>.

We cannot claim that the estimated effects are representative of the whole Nation, and external validity condition might not hold

²⁹We excluded single-sex schools exclusively for boys as well as schools outside Piura Region that could not be reached in a single bus trip.

³⁰Power test calculations were performed by the research team in March 2018. Based on a sample size of 5450 students (109 clusters and 50 number of subjects per cluster), and an intraclass 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)

treatment group (subject to the role model intervention) whereas the other half do not receive the role model intervention. In total 51 and 58 schools were randomly assigned to the treatment and control group, respectively. The visits of female role models only targeted senior-year high school students. Table 1 shows the balanced characteristics of students in the treatment and control groups.

School interventions and female role models. The school visits took place between May and July 2018. We assigned to each female role model at least 3 and at most 7 schools to visit. Role models have a major in i) Civil Engineering, ii) Industrial and Systems Engineering, or iii) Mechanical and Electrical Engineering; they are between 20-24 years old, and they are engineering students in their fourth/fifth year of undergraduate studies, or very recent graduates. On average, a treated school was visited by a single role model.³¹ Randomly assigning role models to schools was not possible since all the role models participated in the intervention on a voluntary basis, and outside of their regular class and work itinerary; however, the allocation of schools' visits was by lottery and any subsequent adjustment was made depending on role models' availability.³²

The role models participated in a training session where they received feedback on their presentations before going to the treatment schools; and most of the role models had previous experience in social events, group projects, and as volunteers in non-profit organizations; therefore, they have leadership abilities and they are expected to perform relatively well as role models in their field of study.

3 Data and Empirical Strategy

3.1 Data

Student follow-up survey. We conducted a post-visit survey in 101 out of the 109 schools (both treatment and control groups) six months after the treatment, in November 2018.³³ Students' answers to the survey were anonymous. Since we do not have access to the students' names or IDs, we are unable to match the survey data with UDEP admissions or the Ministry of Education administrative records. The survey was designed to collect a rich set of information on students' career choices, stereotypes, baseline scores of math, science, and language at high school, demographic characteristics, and family background. It also incorporates students' beliefs about the kinds of jobs associated with women and men, self-perception, self-confidence, knowledge of engineering fields, and economic return.³⁴ The

³¹Two role models visited the treatment schools located in Trujillo and Tumbes, in these cases, only one role model gave the speech 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.

³²The allocation of role models to schools was subject to availability and willingness to travel. We try our best to have a fair distribution of talks in terms of the number of talks and travel distance.

³³In eight schools, we could not conduct the follow-up survey because schools' authorities did not give us the necessary permission.

³⁴A rich survey helps us in the task of identifying the different channels throughout which the intervention has an impact on students' preferences for engineering majors. On one hand, it is possible that the exposure to role models increases students' awareness about different types of engineering and the average salary for an engineer, we refer to this type of mechanism as the information channel throughout the paper. On the other hand, the exposure to role models could increase the student's level of confidence in own math skills (self-concept) and could reduce gender stereotypes

survey was administered in almost all the schools in our sample, (93%, 54 out of 58 schools from the control group, and 47 out of 51 schools from the treatment group).³⁵

The survey was two pages long with 43 short questions, most of them multiple choice ones. The questionnaire asked students for their GPA scores in math, language and science in 10th grade; that is, in the previous academic year.³⁶ We also ask students for their plans to continue higher education after high school, the major they would like to pursue, whether they have already decided where and what major to study, or if they are already registered to start college in the coming academic year. Additionally, we ask students several questions to measure beliefs, perceptions and self-confidence. In first place we asked them to imagine that they have two friends “Javier”, a male; and “Lorena”, a female; and that both of them got 20 (the maximum score in the Peruvian grading system) in math and science at school. We then proceeded to ask them which college major they would recommend to each of them. This question was designed to explore gender bias in STEM conditional on the same math and science skills. In a similar fashion, we introduce to the students a hypothetical successful person currently working in the engineering sector, and we ask students whether the person is more likely to be a woman/man to verify the presence of gender stereotypes.

In order to test if students in the treatment schools have a better knowledge of engineering fields than those in the control schools, we also asked students to list at most five different types of engineering field they know. In addition, we collected information on students’ expectations for the average monthly salary of a college graduate in engineering. To measure student’s self-confidence we ask students if they feel they have the abilities needed to study engineering at college. Finally, we collect data on parental demographic characteristics (i.e., age, education, working status, engineering background), siblings,³⁷ and economic status.³⁸ The survey ends with a question about having taken the 2018 UDEP academic aptitude test. Due to budget constraints, we did not survey the students before the intervention took place. However, we have baseline scores (for math, science, and language) self-reported by the students in the follow-up survey. An indirect advantage of not having a baseline survey is the lower risk of social desirability bias in the follow-up survey answers.

3.1.1 Data Analysis

We have information extracted from the follow-up survey on 5378 senior-year high school students. Of them 56% (2998) were women. 50% (2704) of the students were attending a school assigned to the treatment group. The gender composition of the treatment and control groups is slightly different, but the difference is not statistically significant (58% are women in control schools and 54% are women in

³⁵The 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.

³⁶Math performance was measured using the students’ final course grade on math in grade 10. As these grades were known by students half-year before the role models’ visits took place, we can rule out the possibility that the measure of math academic performance in our paper could have been affected by our interventions.

³⁷Number of siblings, number of siblings by gender, number of siblings by gender and college enrollment, number of siblings by gender and college enrollment in engineering, number of siblings by gender, and Professional Engineer status.

³⁸Housing condition property, fixed assets at home (number of cars, television, computers), internet access.

treatment schools).

In Table 1, we present the balance tests for the combined sample of men and women. Key features to note for this sample is that math baseline high school scores (based on a vigesimal grading system) in the control and treatment groups are very close (14.64 versus 14.51), and the difference is not statistically significant. Students' parents have approximately 13 years of education, students are on average 16 years old, and have 2 siblings. About 95% of them have a working father and 68% of them have a working mother. 15% of students have a father engineer and 3% of them have a mother engineer. The sample is balanced on all characteristics collected. 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 OLS estimates.

In this section, we also discuss the differences in terms of perceptions, beliefs and stereotypes across genders. Given that our data comes from the follow up survey, we only focus on boys and girls in the control group (see Table 2). Approximately 40% of boys in the control group declared planning to study engineering while only 14% of girls in the control group stated the same. In addition, boys and girls in the control group are more likely to consider only males as successful engineers (88% for boys and 61% for girls). Interestingly, while a higher proportion of girls in the control group than boys (71% versus 67%) have already decided which university to attend, girls are less confident than boys in their capabilities to pursue a career in engineering (37% versus 59%).

Interestingly, 52% of boys and 49% of girls suggested engineering to "Lorena" (a hypothetical female friend), an indicator that roughly half of the boys and half of the girls in the control group consider engineering a career suitable for women with high math skills. Also, there are gender gaps in knowledge of engineering. Students, both men and women in the control group on average listed 4 types of engineering they know. However, on average the number of engineering types listed by women is higher than the engineering types listed by men, and the difference is statistically significant at 5%.

Overall, we conclude that the relatively widespread stereotyped perceptions on engineering among girls and boys leaves room for our field experiment to contribute towards updating girls' beliefs about engineering majors.

3.2 Empirical Strategy.

As just mentioned before, we conducted a post-visit survey to measure the effect of the intervention on students' career preferences and perceptions. Using the data from this survey, 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 female 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 whether there are different effects by gender.

We control for student characteristics X_{isc} (including household background). In addition, we add city fixed effects (θ_c) to account for the fact that the randomization was stratified by city (schools within city- half of them received the treatment and half of them did not). Finally, in all our estimations standard errors are clustered at the unit of randomization (school).

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. Approximately, 12% of the schools that were assigned to the treatment group did not receive the visit of female role models. The non-compliance was mostly due to organizational and institutional issues.³⁹ To deal with the non-compliance, we also estimate the 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 A2.

A possible concern is that students in treatment schools may have talked about the role models visits with peers in control schools (i.e. friends in the neighborhood who attend a different school, or siblings attending different schools), which might 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 would be interpreted as a lower bound of the actual impact of the intervention on students’ career preferences.

4 Results

In this section we discuss the intervention impacts on our main outcomes of interest: i) students’ preferences for engineering, ii) student’s self-confidence, self-perception, gender stereotypes and knowledge of engineering, and iii) students’ preferences for other STEM and non-STEM majors.

4.1 Effects on Career Choices: Preferences for Engineering

Table 3 presents the ITT intervention effect on students’ preferences for engineering following the specification of equation (1). The first column shows the effect on students’ preferences not controlling for covariates. Control variables are added gradually in columns 2 to 6. Notice that controlling for covariates does not change the size of the estimates. For the overall sample of women and men, the intervention does not have a statistically significant impact on boys’ and girls’ preferences for engineering.

³⁹Role models were not allowed to enter and to give the speech. With regard to the concern that some students missed classes the day of the intervention, in Peru school attendance rates are high, with students registered in school rarely missing classes. Furthermore, outcomes are not available for all the schools in the treatment and control groups since the follow-up survey was not carried out in 8 schools, nevertheless, this only represents 7% of the total of schools.

Regarding other covariates included in columns 2 to 6 in Table 3, several patterns are worth mentioning (See Table A1, column 1 in the Appendix). On average, girls are 26 percentage points less likely to prefer engineering majors (significant at 1%). Moreover, age and preference for engineering seem to be inversely related. A possible explanation is that older individuals might face both physical and emotional constraints, which limit their abilities to choose or perform well in engineering majors. In addition, students with female siblings, who also study engineering, are 6 percentage points more likely to prefer engineering as well (significant at 5%). Having a father engineer also increases students' preference for engineering, in this case by 4 percentage points. This result validates the presence of peer effects within household members. Owning a house (a proxy of economic status) rises the probability to select engineering in 3 percentage points. Finally, in line with the hypothesis of selection based on comparative advantages, an additional point in the final math course grade (which was taken one year previous to the intervention) leads to a 5 percentage points (significant at 1%) increase in the likelihood of selecting engineering as a preferable career in our follow-up survey. Similarly, students with one additional point in Language (Spanish) are 2 percentage points (significant at 1%) less likely to consider engineering. Hence, comparative advantages in skills play a role when choosing what career to study.

Taking into account the recent evidence on heterogeneous effects in the literature on role models and STEM career choices, in what follows we will explore if our intervention had heterogeneous effects for different ranges of students math ability distribution, as measured by grade 10th math GPA. We will also look for local effects, that is, if the role models were more likely to affect students who reside closer to the role models university.

Heterogeneous effects as a function of math ability and region of residence. To shed light on how the intervention might have impacted boys and girls differently depending on their math academic aptitude, we split the sample into four groups or quartiles. These four groups or quartiles are constructed based on the students self-reported 10th grade math GPA. 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. Since baseline math scores reported by students are discrete, the quartiles constructed do not have similar sizes.⁴⁰

Figure 4 shows the proportion of senior-year high school students (11th graders in the U.S.) who listed engineering as their most preferred option to study at any university after high school graduation, separately for boys and girls and over quartiles of self-reported math scores in grade 10th. As we can observe, the percentage of students who prefer an engineering program increases with math scores. This reflects a specialization strategy, students who are strong in math find math-intensive majors more attractive. As we can also observe, our intervention seems to have a positive impact on preferences for engineering among female students in the top quartile of the math distribution. For this subgroup

⁴⁰32% of the observations lay in the first, 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, top, quartile.

of female students, the probability to prefer engineering increases by 7.3 percentage points (significant at 10%) if the school was assigned to the role model talks, which corresponds to a 36 percent increase from a baseline of 20 percent. Especially salient is the fact that among the 25 percent top achievers in math, the gender gap in preference for engineering is 35 percentage points and the intervention reduces it by 6.5 percentage points, which corresponds to an 18.6 percent reduction from the baseline. The figure also shows that among males, the intervention does not seem to have any effect on engineering preferences among boys in the top math quartiles; however there is a positive although not statistically significant among boys in lower quartiles. We will discuss this specific result in the next sections in the paper. In figure 5 we restrict the sample only to schools in the Piura region, where UDEP influence and prestige are expected to be stronger. In this case the effect for girls in the top math quartile becomes stronger, (ITT of 15.7 percentage points) and highly statistically significant (in this case at 1 percent level).

Table 4 shows the ITT treatment effect estimates for the sub-sample of students in the upper quartile of baseline math scores. As we can observe in Table 4, the ITT estimated coefficients for females in the top quartile of the math distribution are positive and statistically significant at 5%. While the estimated ITT coefficients among boys are very close to zero and not statistically significant. However the interaction terms in this case are not statistically significant (except for column 4 at the 10% level), and therefore we cannot reject the null of no different ITT effects among genders.

As mentioned before, our role models are senior engineering students or recent engineering graduates from UDEP, and during their 20-minute talks, they clearly stated their connection with this university. In this sense, they may have been more effective (i.e. better at capturing the students attention) in schools within areas in which the university has a relatively high level of influence, reputation and/or recognition. In fact, UDEP is recognized as the leading and more prestigious university in the Piura region, and this influence and prestige also reach 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 UDEP incoming 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.⁴¹ It is possible then that given that the role models clearly stated their connection with UDEP, their influence may have been stronger in areas in which UDEP is the regional leader. Taking this into account, in Table 5 the sample is further restricted to high-ability students in schools located in Piura. Finally, in Table 6 we perform a similar analysis only including schools located in Piura and their neighbouring regions of Tumbes and Lambayeque.⁴²

Our findings in Tables 5 and 6 indicate that the school interventions were more effective at steering high math skilled girls (upper quartile) towards engineering fields, specifically for those high ability girls in schools located geographically close to the role models' local university. High ability girls in

⁴¹For 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.

⁴²Tumbes is the region located to the north of Piura while Lambayeque borders the Piura region to the south.

the fourth quartile of baseline math scores, enrolled in classes in schools located in Piura, and exposed to female role models are 14.1 percentage points more likely to prefer engineering (78% increase from a baseline of 18%) than female students in the control group [See Table 5, column 1]. The size of the estimate remains stable after the inclusion of control variables, and the interaction coefficient term between the treatment and female indicators is always statistically significant at the 1% level, so we can 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 than those in Table 5, but remain statistically significant at the 1% level. The results in Table 5 and 6 also confirm that the intervention does not push high-ability boys towards engineering. An obvious explanation for this is that high math ability boys are already selecting engineering careers.

In Table 7 we assess the effect of the role models' visits on low-ability students, those in the lowest quartile of baseline math score. As we can observe the related coefficients are relatively low and not statistically significant. In Table 8 and Table 9, we explore the ITT effects on low ability students (bottom 25% percentile) for the Piura region only and then adding the Lambayeque and Tumbes regions respectively (bottom 25 percentile). While we do find some effects for males in the lowest math quartile, it only happens for some of the specifications for the Piura and neighboring regions sample, the point estimates for these effects are 5 to 6 p.p. lower than the point estimates for females in the top quartile, and in the majority of cases only statistically significant at the 10% level. As role models emphasized that personal qualities other than being a math genius were required to pursue a career in engineering, such as imagination and creativity, some low math ability boys may have adjusted their engineering preferences as a result of this specific message.

Table 10 summarizes the ITT estimates for our role model interventions on 11th graders preferences for engineering separately by gender, geographical location and quartile of math performance in 10th grade. In Panel A of table 10, the ITT estimates correspond to the full sample, while in panel B of table 10 we restrict the analysis to schools in the region of Piura and the adjacent regions of Tumbes and Lambayeque. Overall, with respect to engineering career preferences, our intervention increased the likelihood that a female student located geographically close to UDEP in the upper math quartile stated engineering as her most preferred option by 13.1 percentage points (significant at 1%). No effects for female students in the 1st, 2nd, and 3rd quartile were found in any specification.⁴³

4.2 Perceptions, Self-Concept, and Gender Stereotypes.

In order to isolate the potential mechanisms driving our baseline results, in the follow-up survey we asked students whether they agree or not with several statements intended to measure students' self-confidence and gender stereotypes.

We begin our analysis with Table 12, which reports the estimated ITT effects on students self-confidence

⁴³We have also calculated probit marginal effects, which resulted to be very similar to the OLS estimates and can be provided under request.

in their own math skills to pursue engineering majors at college. As we can observe, treated female students in the top 25 percentile of the math score distribution and in schools within UDEP areas of higher influence experienced a 12.5 (significant at 5%) percentage point increase in the level of self-confidence regarding their own abilities to pursue engineering fields. This specific result strongly suggests that exposure to role models positively influenced high math ability girls' self-confidence, and that this increased self-confidence led to an increase in preferences for engineering studies. Interestingly, we also observe a statistically significant effect for high ability boys, but with the opposite sign. High math ability treated boys appear to be less confident in their math skills to pursue an engineering major. As pointed before, one of the key messages in the role models talks was that you do not need to be a mathematical genius to major in engineering. This message may have influenced these boys perceptions on the role of high math skills to succeed in engineering. However, it did not affect their preferences to major in engineering fields.

In order to further explore for potential mechanisms driving our baseline results, in tables 13 to 16, we evaluate whether or not our role model intervention also affected gender stereotypes. In addition, we also assess whether treated students have more information about engineering fields and about the earnings of recent college graduates from engineering.

In our follow up survey we described a person who happens to be successful engineer and asked students whether they thought that person was more likely to be male or female. We constructed an indicator that took the value of one if the student responded that the person was more likely to be male, and zero otherwise. Table 13 presents the results related to this question. In general treated girls in our sample are less likely to indicate that the successful engineer is male, but the estimated coefficients are relatively small and only statistically significant when we group girls in the two lowest math ability quartiles together. The estimated ITT coefficients are also negative for males, but relatively small in size and in no case we were able to detect statistical significance.

We also presented students in our sample with a hypothetical male and female student, and describe both as high math ability ones. We asked students in our sample to suggest a major to each of these individuals. The results for this specific question are presented in Table 14. Treated girls were not more likely to recommend engineering majors to the female student than control ones. In the case of treated boys, those in the second lowest quartile were more likely to suggest an engineering major to the female student. As we have shown before, we find some, though weak evidence suggesting our treatment also affected the engineering preferences of low ability boys.

Regarding information about engineering. We first ask students in our sample to list up to five engineering majors. Surprisingly, treated girls in the top math quartile listed less majors than control ones. While these results are at first counterintuitive -given the nature of our baseline results as well as the results related to females confidence to pursue engineering majors- they may also suggest that treated females were more likely to focus their attention on a very specific (and therefore reduced) set of engineering fields. In any case, we do not have a conclusive interpretation for this result. We also ask students about the expected monthly salary for a recent graduate in engineering. In general we do not

find conclusive evidence on the intervention having an effect on this indicator; however, treated boys in the second lowest quartile located within UDEP area of influence reported a statistically significant higher salary than control ones. The pattern of preferences and perceptions for treated boys in this quartile, clearly suggest that, if any, they were listening carefully to the role model talk.

4.3 Other majors choices (non-STEM and non-engineering STEM)

In the previous section, we found that treated female students with high math skills increased their preferences for engineering, which is a relatively high-paid STEM discipline, compared to those in the control group. This section explores how the intervention affected students' preferences for other majors, both non-STEM and STEM ones other than engineering. For some, the intervention might be interpreted as counter-productive if it encouraged some students to pursue non-STEM careers, given the lower salary perceived by professionals in some areas in the non-STEM sector.

As we can observe in Table 11, the intervention only 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 chose a non-STEM field. Also note that the absolute value of the estimated coefficients are relatively similar to those observed for high math aptitude girls in Table 10. This clearly indicates that our intervention is just moving the preferences of high math aptitude girls from non-stem majors to majors in engineering, and that it did no affect the preferences for non-STEM major among any other type of individuals in our study. In other words, our intervention seems to be promoting a reallocation of talent and capabilities at the margins where this reallocation is likely needed.

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 may be related to the extremely low share of students who prefer STEM majors different than engineering in the Peruvian context.⁴⁴

5 Robustness Checks

5.1 Alternative Measures of Ability: Science and Math

In our baseline estimation we explored differential ITT effects as a function of students math ability, which is an indicator of students capacity to major in engineering at college. In this section, in addition to 10th grade math scores, we also consider 10th grade science scores, as competence in science may also be an indicator for the student capacity to pursue a degree in engineering. In first place, we construct a dummy variable that equals one if the student ranked in the top 25 percentile in both courses, math and science in 10th grade, and zero, otherwise. As we can observe, the ITT effect is positive and statistically significant for the sub-sample of female students within UDEP main regional

⁴⁴These results are available upon request.

area of influence who belong to both, math and science, top quartiles (See Appendix Table A3). In line with our main results, high science and math female students are 21 percentage points (significant at 1%) more likely to prefer engineering as a result of our role models intervention.

We have also explored other performance combinations related to high school math and science. In particular we explored the intervention ITT effects on students who are in the top math quartile but not in the top science quartile and vice versa. Our results show that the intervention did not increase the preferences for engineering among girls in these groups. Moreover, if the female student was in the top quartile of the science distribution but not in the math one, the estimated ITT is actually negative and statistically significant. These results suggest that both, math ability and science ability, are needed for the development of preferences among girls towards STEM fields.

5.2 ECE math scores

Schools in our sample may differ in terms of academic quality and grading policies and this may affect the interpretation of our math quartiles. Does a high math GPA in 10th grade really indicate a high level of math ability? In order to overcome this issue, we control by school academic quality using the *Evaluación Censal de Estudiantes* (ECE), which is a standardized national examination administered to students in the second grade of secondary education (8th graders in the US). The ECE is administered in all public and private schools in Peru to find out what and how much students are learning in math and language subjects.

In 2015, the students in our sample were in 8th grade. Hence, we use the 2015 ECE school level results to control for average school ECE math scores in the regressions, an indicator of school academic quality. Table A4 in the Appendix shows the ITT treatment effect estimates for females and males over different quartiles of baseline math scores after controlling for ECE math scores. The ITT estimated coefficient for female students in local schools and upper quartile is positive and statistically significant at 5% (9.5 pp); however, it is lower in size compared to its equivalent in Table 6 of 13.1 pp. The difference in the estimates can be attributed to the additional effect of average school math ECE scores on students' preferences for engineering. We expect students attending schools with greater average ECE math scores to be more likely to prefer engineering majors, *ceteris paribus*.

6 Other Heterogeneous Effects

6.1 Identity of the Role Models and School Distance

We also investigate how role models' characteristics might have influenced decisions to pursue engineering fields. For example, it is very likely that high school students are attracted by role models engineers, who have graduated from the same high school, and it is this particular group of role models that has the higher impacts on students' career choices. Unfortunately, our dataset does not contain any case where role models gave the speech in their own high school. As an alternative method, we calculate

the distance (in km) between the role model’s high school and the school she visited, and we divide the sample into three groups: i) distance less than 4 km, ii) distance less than 2 km, iii) distance less than 1 km. According to our findings, students in high schools exposed to role models who graduated from a close school (i.e. school located less than 1km) are 8.4 (significant at 5%) percentage points more likely to pursue engineering majors. (See Appendix Table A5).

Our intuition is that a short distance between the role models’ school of graduation and the school they visited makes it more likely that both role models and high school students identified with each other. Role model visits seem to be more effective when high school students feel closer to the role models.

6.2 Close Distance to UDEP

As we have already shown, the ITT effects of our intervention are stronger among high math ability girls who reside within Piura and in the neighbouring regions of Lambayeque and Tumbes. This area is considered as the historical influence area of UDEP. In this section we further investigate whether students in schools located geographically close to Universidad de Piura are more likely to be encouraged to pursue Engineering fields. Using longitude and latitude coordinates of the location of the schools in our sample and the location of UDEP, we calculate the distance in kilometers (km). We expect that a close distance UDEP-school increases the probability for students to be attracted by the role models engineers from UDEP, and this might be attributed to the salience of the university around the area.

Tables A6-A11 in the Appendix shows how the treatment affects students’ preferences for Engineering depending on the distance of the school from UDEP. High-ability women in the top 25 percentile of math scores are 17.2 pp (significant at 1%) more likely to prefer Engineering after a role model exposure if they come from a school located less than 43 km from UDEP. (Column 6, Table A6.). In addition, the estimate is close to zero and no statistically significant for high-ability women in schools located far from UDEP (equal to or more than the sample median of 43 km). The coefficient on the interaction term is statistically significant. Hence, we reject the null hypothesis for equal ITT between high math talented women in near and far schools. A similar analysis but for men in the bottom quartile of math scores is presented in Table A7. Overall low ability men’s predilection for engineering programs increases after the talks in schools situated less than 43 km from UDEP. Men in schools located 43 km or more from UDEP are negatively impacted by the role model visits. In Tables A8-A11 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.

Although the distance between schools and the university (UDEP) is an important determinant to prefer engineering programs, there may be other uncontrolled determinants in the regressions that would also influence the probability of liking engineering such as having funding (i.e. scholarships) to pursue Engineering fields in other universities even if they are located far from the place of residence of the students. Because we do not have information on other relevant factors that could indirectly

impact students' proclivity towards Engineering fields, our results in this section should be taken with caution.

6.3 Role Model's Major

Our role models' majors of study are industrial engineering, civil engineering, or mechanical engineering. During the visits, role models indicate their field of engineering to the students, which allows us to explore heterogeneous effects of the visits on preferences for different types of engineering.

In Table A12 in the Appendix, we assess how different types of engineering appeal to girls. High ability girls are more interested in industrial engineering or civil engineering. Column 3 of Table A12 shows that the treatment increased preferences for civil engineering in 5.2 percentage points (significant at 1%) for the subgroup of high ability students (4th quartile). Positive and stronger estimates are found for high-ability girls in schools relatively close to UDEP (6.3 pp, significant at 1%). Additionally, high-ability girls within UDEP traditional area of influence (above median math) increase their preferences for industrial engineering by 4.9 percentage points (statistically significant at 1%) after exposure to role models.

Role models have a major influence on female university choices, and the majors of role models could nudge female students towards the same major. Hence, we explore our same treatment on a different dependent variable, which equals one if the student stated any of the role models' engineering majors (i.e. industrial, civil, or mechanical) and zero, otherwise. Table A13 in the Appendix uses the same specification of equation (1), but it replaces the dependent variable with a preference for any of the three types of engineering. Overall, girls in the top quartile of baseline math scores were positively affected by the intervention. The school visits increased high ability girls' preferences for any of the three types of engineering: industrial and system engineering, civil engineering, mechanical engineering, in 10.4 percentage points (significant at 5%). In addition, the likelihood to prefer any of these three types of engineering increased by 13.4 percentage points (significant at 1%) for high-ability female students within UDEP traditional area of influence. We attribute these findings to the identity of the role models; in particular the major of study is an important feature observed by the students during the talks.

7 Conclusion

Based on a randomized field experiment at the high school level, this paper provides empirical evidence that low-cost interventions that expose senior-year high school students to female role models are effective, and can potentially mitigate preconceived ideas of high school students that STEM fields are only suitable for men, with broader implications for girls' educational choices at higher education.

Using a randomized school-based intervention in Peru, which exposed senior-year high school students to a 20-minute intervention, we investigate the causal impact of female role models on students' perceptions

and career choices. We find that female role models mitigate the gender stereotypes associated with careers as engineering, for girls high school students. Female students with a strong math academic background exposed to female role models were more likely to project themselves into STEM careers, specifically engineering due to the reduction of gender stereotypes and the increase in self-concept. The effects are strong and large, given the baseline levels. In particular, the likelihood that a local female senior-year high school student in the upper quartile of the math score distribution would end up choosing Engineering increased in 71% as a result of the intervention.

In the Peruvian context, the female enrollment rate in Science, Mathematics, and Statistics (STEM) is 30% which is not far from enrollment rates observed in other countries. In Latin American countries such as Colombia and Mexico, the female enrollment rate in STEM is between 47% -53%, in Brazil the range is between 53% -59% while in Chile and Argentina the presence of women in Science is less than 47%. Worldwide only 8% of the female student population is enrolled in STEM (UNESCO, 2017). In addition, looking at enrollment rates in engineering, in Brazil and Mexico the percentage of women enrolled in engineering is roughly 35% and 30%, respectively, a setting close to the Peruvian context where only 24% of women select engineering. Similarly to the Peruvian context, the female enrollment rate in engineering is the lowest worldwide. While regional and country differences in female participation in STEM studies are observed and this heterogeneity suggests the presence of contextual factors determining the likelihood that girls and women engage in these fields, we consider that a low-cost intervention similar to ours could also rise preferences towards engineering fields in similar contexts in Latino America.

An extension of our study would analyze possible determinants for low-ability students' enrollment in STEM. More research is needed to examine whether role models with a more diverse background in terms of age, experience mentoring, major of study, gender, ethnicity, university attended, or occupation could be more effective to lower-achieving and higher-achieving students. For example, our plan is to replicate our intervention using male role models as well in the future. This would allow us to investigate whether the gender of the mentor is an important determinant to encourage mentees towards STEM disciplines.

References

- Ashraf, N., Bau, N., Low, C. & McGinn, K. (2020), 'Negotiating a better future: How interpersonal skills facilitate intergenerational investment', *The Quarterly Journal of Economics* **135**(2), 1095–1151.
- Avvisati, F., Gurgand, M., Guyon, N. & Maurin, E. (2014), 'Getting parents involved: A field experiment in deprived schools', *Review of Economic Studies* **81**(1), 57–83.
- Bayer, A. & Rouse, C. E. (2016), 'Diversity in the economics profession: A new attack on an old problem', *The Journal of Economic Perspectives* **30**(4), 221–242.

- Beaman, L., Duflo, E., Pande, R. & Topalova, P. (2012), ‘Female leadership raises aspirations and educational attainment for girls: A policy experiment in india’, *Science* **335**(6068), 582–586.
- Bear, J. B. & Woolley, A. W. (2011), ‘The role of gender in team collaboration and performance’, *Interdisciplinary science reviews* **36**(2), 146–153.
- Bernard, T., Dercon, S., Orkin, K. & Taffesse, A. (2014), ‘The future in mind: Aspirations and forward-looking behaviour in rural ethiopia’, *Centre for Economic Policy Research London* .
- Bettinger, E. P. & Long, B. T. (2005), ‘Do faculty serve as role models? the impact of instructor gender on female students’, *American Economic Review* **95**(2), 152–157.
- Blau, F. D. & Kahn, L. M. (2017), ‘The gender wage gap: Extent, trends, and explanations’, *Journal of Economic Literature* **55**(3), 789–865.
- Bottia, M., E.Stearns, Mickelson, R., Moller, S. & L.Valentino (2015), ‘Growing the roots of stem majors: Female math and science high school faculty and the participation of students in stem’, *Economics of Education Review* **45**, 14–27.
- Breda, T., Grenet, J., Monnet, M. & van Effenterre, C. (2020), ‘Do female role models reduce the gender gap in science?: Evidence from french high schools’, *IZA Institute of Labor Economics, Discussion Paper Series IZA DP No. 13163* .
- Brown, C. & Corcoran, M. (1997), ‘Sex-based differences in school content and the male-female wage gap’, *Journal of Labor Economics* **15**(3), 431–465.
- Buser, T., Niederle, M. & Oosterbeek, H. (2014), ‘Gender, competitiveness and career choices’, *Quarterly Journal of Economics* **129**(3), 1409–1447.
- Canes, B. J. & Rosen, H. S. (1995), ‘Following in her footsteps? faculty gender composition and women’s choices of college majors’, *Industrial and Labor Relations Review* **48**(3), 486–504.
- Carrell, S., Page, M. & West, J. (2010), ‘Sex and science: How professor gender perpetuates the gender gap’, *The Quarterly Journal of Economics* **125**, 1101–1144.
- Correll, S. J. (2001), ‘Gender and the career choice process: The role of biased self-assessments’, *American Journal of Sociology* **106**(6), 1691–1730.
- Dee, T. S. (2007), ‘Teachers and the gender gaps in student achievement’, *Journal of Human Resources* **42**(3), 528–554.
- Del Carpio, L. & Guadalupe, M. (2018), ‘More women in tech? evidence from a field experiment addressing social identity’, *CEPR Discussion Paper DP13234* .
- Diekmann & M.Steinberg (2013), ‘Navigating social roles in pursuit of important goals: A communal goal congruity account of stem pursuits’, *Social and Personality Psychology Compass* **7**(7), 487–501.

- Eble, A. & Hu, F. (2017), ‘Child beliefs, societal beliefs, and teacher-student identity match’, *CDEP-CGEG Working Paper* **43**.
- Ellison, G. & Swanson, A. (2010), ‘The gender gap in secondary school mathematics at high achievement levels: Evidence from the american mathematics competitions’, *Journal of Economic Perspectives* **24**(2), 109–128.
- Ellison, S. F. & Mullin, W. P. (2014), ‘Diversity, social goods provision, and performance in the firm’, *Journal of Economics and Management Strategy* **23**(2), 465–481.
- Emerson, T. L., McGoldrick, K. & Mumford, K. J. (2012), ‘Women and the choice to study economics’, *The Journal of Economic Education* **43**(4), 349–362.
- Ferrara, E. L., Chong, A. & Duryea, S. (2012), ‘Soap operas and fertility: Evidence from brazil’, *American Economic Journal: Applied Economics* **4**(4), 1–31.
- Flory, J. A., Leibbrandt, A. & List, J. A. (2014), ‘Do competitive workplaces deter female workers? a large-scale natural field experiment on job entry decisions’, *The Review of Economic Studies* **82**(1), 122–155.
- Gneezy, U., Niederle, M. & Rustichini, A. (2003), ‘Performance in competitive environments: Gender differences’, *Quarterly Journal of Economics* **118**(3), 1049–1074.
- Hardt, D., Nagler, M. & Rincke, J. (2020), ‘Can peer mentoring improve online teaching effectiveness? an rct during the covid-19 pandemic’, *Cesifo 8671 Working paper* .
- Hoffmann, F. & Philip, O. (2009), ‘A professor like me: The influence of instructor gender on college achievement’, *Journal of Human Resources* **44**(2), 479–492.
- Hoogendoorn, S., Oosterbeek, H. & van Praag, M. (2013), ‘The impact of gender diversity on the performance of business teams: Evidence from a field experiment’, *Management Science* **59**(7), 1514–1528.
- Hsieh, C., Hurst, E., Jones, C. & Klenow, P. (2019), ‘The allocation of talent and u.s. economic growth’, *Econometrica* **87**(5), 1439–1474.
- Hyde, J. (2005), ‘The gender similarities hypothesis’, *American Psychologist* **60**(6), 581–591.
- Kahn, S. & Ginther, D. (2017), ‘Women and stem’, *NBER Working Paper Series* .
- Kipchumba, E. K., C.Porter, Serra, D. & Sulaiman, M. (2021), ‘Influencing youths’ aspirations and gender attitudes through role models: Evidence from somali schools’, *Working Paper* .
- Kofoed, M. S. & McGovney, E. (2019), ‘The effect of same-gender or same-race role models on occupation choice evidence from randomly assigned mentors at west point’, *Journal of Human Resources* **54**(2), 430–467.

- Lim, J. & Meer, J. (2017), ‘The impact of teacher-student gender matches: Random assignment evidence from south korea’, *Journal of Human Resources* **52**(4), 979–997.
- Lim, J. & Meer, J. (2019), ‘Stereotypes, role models, and the formation of beliefs’, *Journal of Human Resources* **54**(2), 430–467.
- Lim, J. & Meer, J. (2020), ‘Persistent effects of teacher-student gender matches’, *Journal of Human Resources* **55**(3), 809–835.
- Macphee, D., Canetto, S. & Farro, S. (2013), ‘Academic self-efficacy and performance of underrepresented stem majors: Gender, ethnic, and social class patterns’, *Analyses of Social Issues and Public Policy* **13**(1), 347–369.
- Neumark, D. & Gardecki, R. (1998), ‘Women helping women? role model and mentoring effects on female ph.d. students in economics’, *Journal of Human Resources* **33**(1), 220–246.
- Nguyen, T. (2008), ‘Information, role models, and perceived returns to education: Experimental evidence from madagascar’, *Manuscript* .
- Niederle, M. & Vesterlund, L. (2007), ‘Do women shy away from competition? do men compete too much?’, *Quarterly Journal of Economics* **122**(3), 1067–1101.
- Niederle, M. & Vesterlund, L. (2010), ‘Explaining the gender gap in math test scores: The role of competition’, *Journal of Economic Perspectives* **24**(2), 129–144.
- Nollenberger, N., Rodriguez-Planas, N. & Sevilla, A. (2016), ‘The math gender gap: The role of culture’, *American Economic Review* **106**(5), 257–261.
- Ortiz-Ospina, E. & Roser, M. (2018), ‘Economic inequality by gender’, *Our World in Data* .
- Porter, C. & Serra, D. (2020), ‘Gender differences in the choice of major: The importance of female role models’, *American Economic Journal: Applied Economics* **12**(3), 226–254.
- Reuben, E., Wiswall, M. & Zafar, B. (2017), ‘Preferences and biases in educational choices and labour market expectations: Shrinking the black box of gender’, *The Economic Journal* **127**(604), 2153–2186.
- Riley, E. (2017), ‘Role models in movies: the impact of queen of katwe on students’ educational attainment’, *Technical report, Centre for the Study of African Economies, University of Oxford* .
- Rothstein, D. S. (1995), ‘Do female faculty influence female students’ educational and labor market attainments?’, *Industrial and Labor Relations Review* **48**(3), 515–530.
- S.Cheryan, Plaut, V., Handron, C. & Hudson, L. (2013), ‘The stereotypical computer scientist: Gendered media representations as a barrier to inclusion for women.’, *Sex Roles Springer Science+Business Media New York* **69**, 58–71.

- Signorella, M., Bigler, R. & Liben, L. (1993), 'Developmental differences in children's gender schemata about others: a meta-analytic review', *Developmental Review* **13**, 147–183.
- Spelke, E. (2005), 'Sex differences in intrinsic aptitude for mathematics and science: A critical review', *American Psychologist* **60**(9), 950–958.
- UNESCO (2017), 'Cracking the code: Girls and women's education in science, technology, engineering, and mathematics (stem)', *Technical report* .
- Weinberger, C. J. (1999), 'Mathematical college majors and the gender gap in wages', *Industrial Relations* **38**(3), 407–413.

Figures and Tables

Figure 1: Enrollment in Engineering at UDEP

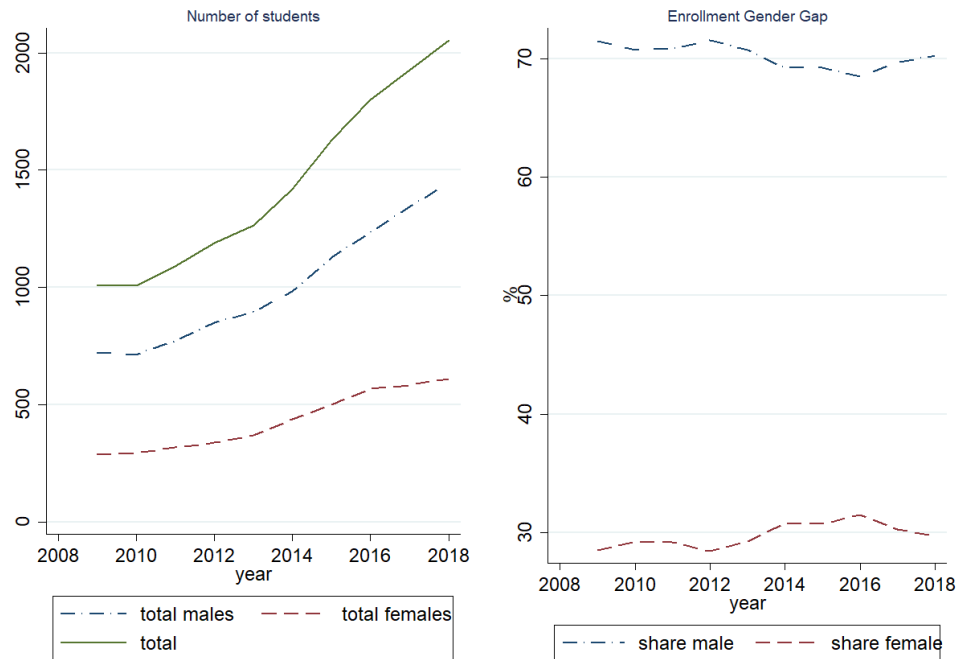


Figure 2: Enrollment in Engineering at UDEP: First-semester students

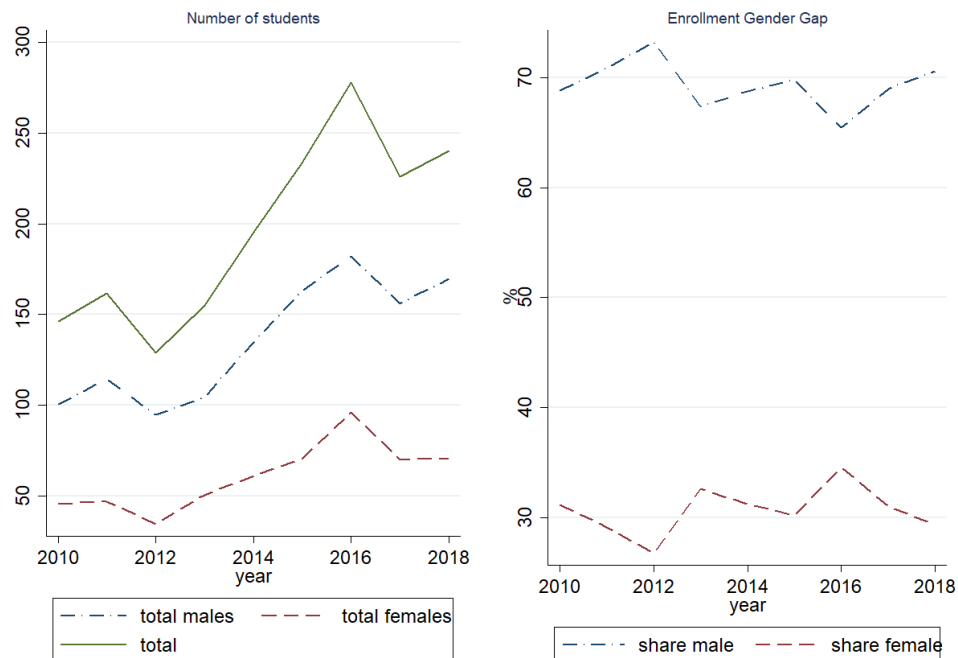


Figure 3: Program Evaluation Timeline

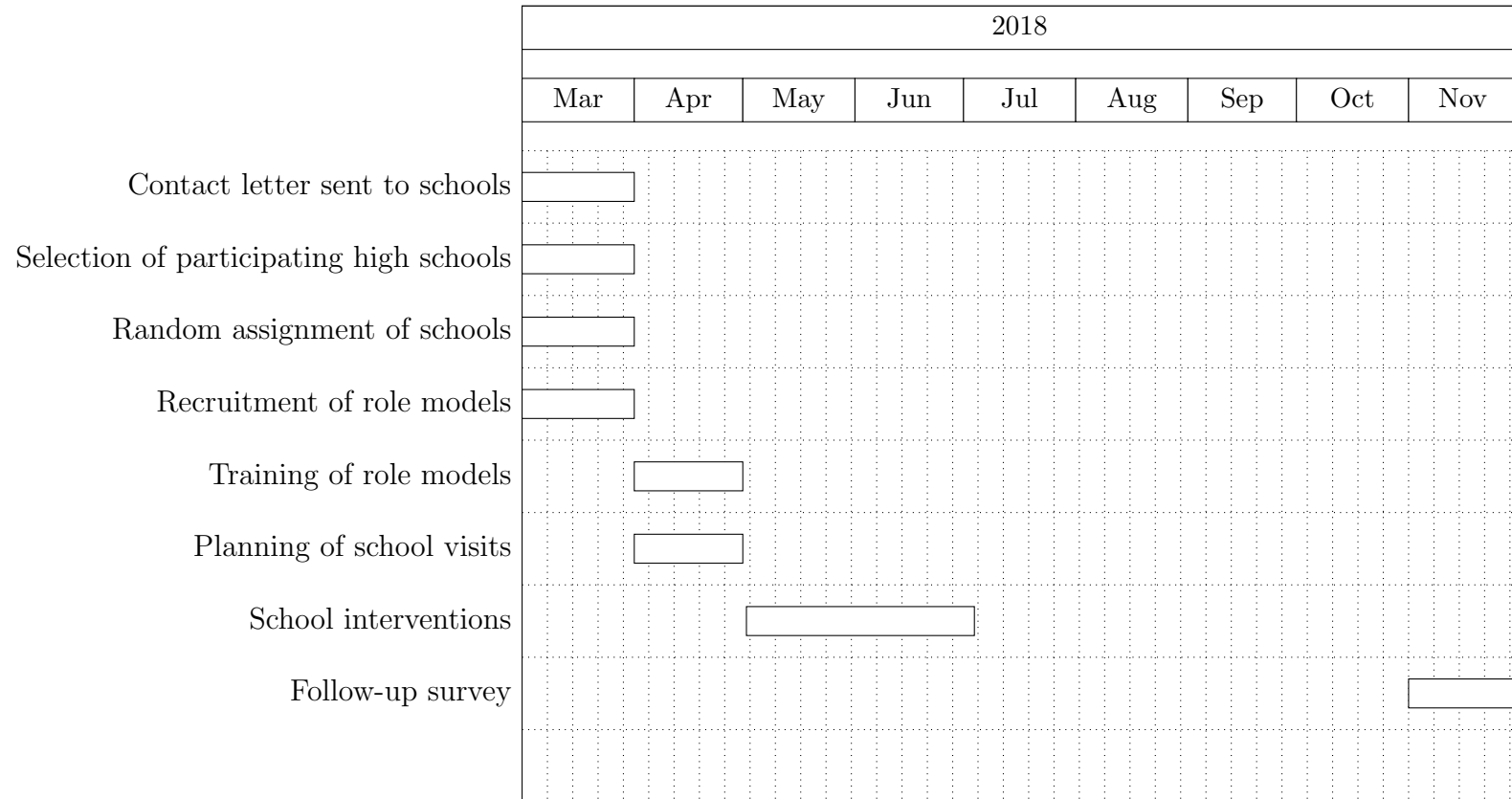
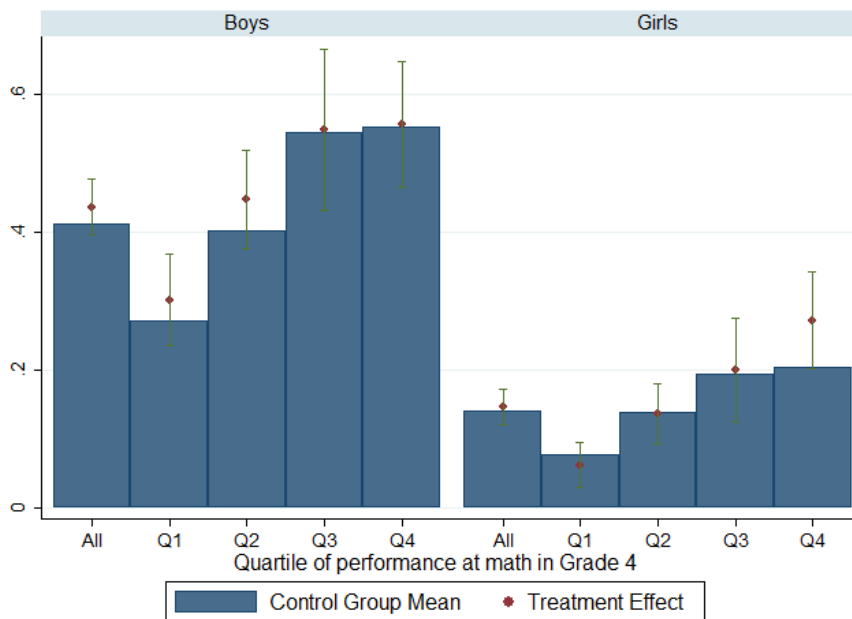
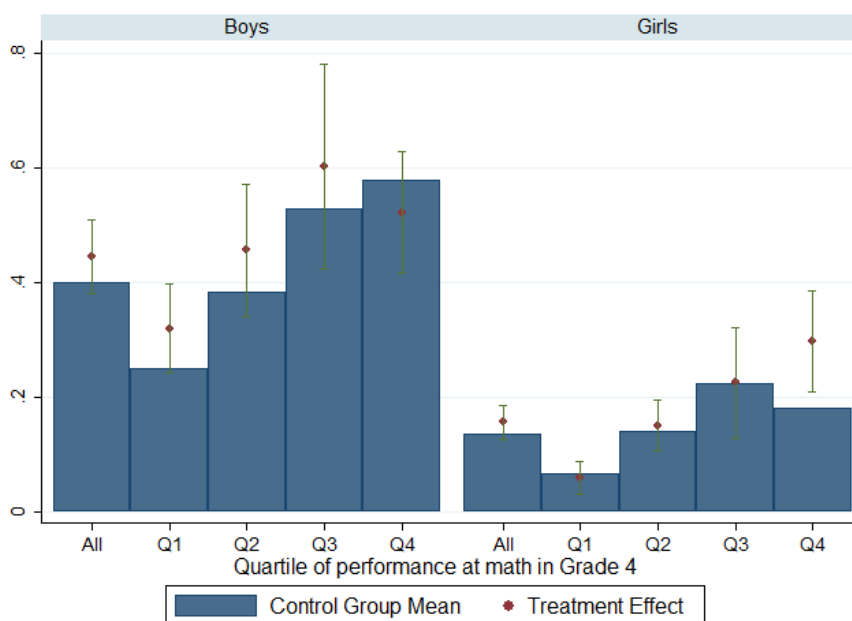


Figure 4: Senior-Year High School Students- Preference for Engineering by Student Gender and Quartile of Baseline Math Score



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 5: Senior-Year High School Students- Preference for Engineering by Student Gender and Quartile of Baseline Math Score: Only Piura



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: Treatment-Control Balance

	Control Group (1)	Treatment Group (2)	Difference T-C (3)	p-value (4)
Full Sample				
Female	0.575	0.540	-0.058	0.330
Age	16.232	16.266	0.018	0.393
Math	14.641	14.510	-0.083	0.621
Language	15.589	15.072	-0.333	0.100
Science	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
Female sibling engineer	0.044	0.041	-0.003	0.599
Number of Observations	2694	2704		
Test of joint significance	F-stat: 1.11 (p-value: 0.358)			

Notes: Column 1 and column 2 report the sample mean for students in the control and treatment group, respectively. The sample is restricted to students in the treatment and control groups who answered the post-treatment survey. Column 3 displays the estimate on the treatment dummy in a regression of each variable on treatment. P-values for the statistical 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 comes from a follow-up survey implemented in 18 cities of Peru to senior-year high school students in November 2018.

Table 2: Difference in preferences for Engineering and perceptions: By gender

Sample:	(1) Boys	(2) Girls	(3) Diff
Pref Eng	0.405 (0.015)	0.139 (0.009)	0.266*** (0.017)
Male_success	0.883 (0.010)	0.609 (0.013)	0.274*** (0.016)
self_confidence	0.585 (0.015)	0.367 (0.012)	0.219*** (0.019)
university_study	0.670 (0.014)	0.711 (0.012)	-0.041** (0.018)
lorena_eng	0.520 (0.015)	0.492 (0.013)	0.028 (0.020)
count_eng	4.323 (0.031)	4.403 (0.023)	-0.081** (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 3: The Effect of Exposure to Role Models on students' career choices

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 (Treatment*female)	-0.023	-0.024	-0.024	-0.024	-0.008	-0.008
	(0.027)	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
ITT female:	0.013	0.011	0.011	0.010	0.008	0.010
Treatment + Interaction						
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	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
Female sibling engineer	No	No	No	No	No	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. 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 4: The Effect of Exposure to Role Models on students' career choices (high ability students)

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	-0.003 (0.043)	0.005 (0.047)	0.001 (0.047)	-0.004 (0.046)	-0.006 (0.049)	-0.002 (0.049)
Female	-0.335*** (0.031)	-0.338*** (0.031)	-0.338*** (0.031)	-0.331*** (0.030)	-0.309*** (0.037)	-0.307*** (0.038)
Interaction (Treatment*female)	0.083 (0.055)	0.082 (0.054)	0.083 (0.054)	0.091* (0.054)	0.096 (0.059)	0.093 (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
Parent Engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent Education	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
Female sibling engineer	No	No	No	No	No	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. 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 5: The Effect of Exposure to Role Models on students' career choices 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 (0.056)	-0.030 (0.058)	-0.037 (0.056)	-0.031 (0.057)	-0.026 (0.059)	-0.012 (0.057)
Female	-0.360*** (0.045)	-0.362*** (0.045)	-0.361*** (0.043)	-0.352*** (0.042)	-0.316*** (0.048)	-0.296*** (0.048)
Interaction (Treatment*female)	0.177** (0.069)	0.179** (0.068)	0.177*** (0.064)	0.176** (0.067)	0.171** (0.070)	0.153** (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
Parent Engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent Education	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
Female sibling engineer	No	No	No	No	No	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. 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 6: The Effect of Exposure to Role Models on students' career choices 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 (0.049)	-0.039 (0.049)	-0.042 (0.049)	-0.039 (0.049)	-0.049 (0.051)	-0.043 (0.050)
Female	-0.374*** (0.032)	-0.373*** (0.033)	-0.371*** (0.032)	-0.370*** (0.033)	-0.358*** (0.039)	-0.354*** (0.042)
Interaction (Treatment*female)	0.163*** (0.058)	0.162*** (0.057)	0.162*** (0.056)	0.169*** (0.058)	0.179*** (0.064)	0.174*** (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
Parent Engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent Education	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
Female sibling engineer	No	No	No	No	No	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. 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 7: The Effect of Exposure to Role Models on students' career choices (low ability students)

Dep. Variable:	Prefer Engineering					
Sample:	1st Q	1st Q	1st Q	1st Q	1st Q	1st Q
	math	math	math	math	math	math
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0323 (0.0333)	0.0309 (0.0369)	0.0330 (0.0368)	0.0390 (0.0354)	0.0224 (0.0350)	0.0196 (0.0355)
Female	-0.190*** (0.0243)	-0.194*** (0.0269)	-0.193*** (0.0268)	-0.201*** (0.0254)	-0.192*** (0.0247)	-0.195*** (0.0251)
Interaction	-0.0478 (0.0379)	-0.0504 (0.0413)	-0.0545 (0.0410)	-0.0543 (0.0398)	-0.0389 (0.0397)	-0.0387 (0.0398)
ITT female: Treatment + Interaction	-0.016	-0.020	-0.021	-0.015	-0.017	-0.019
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	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
Female sibling engineer	No	No	No	No	No	Yes
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

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences. Sample is restricted to low ability students (first quartile of baseline math scores), who answered the survey. 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 8: The Effect of Exposure to Role Models on students' career choices (low ability students) in Piura schools

Dep. Variable:	Prefer Engineering					
Sample:	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 (0.042)	0.068 (0.047)	0.066 (0.046)	0.073* (0.043)	0.058 (0.044)	0.051 (0.044)
Female	-0.181*** (0.033)	-0.184*** (0.038)	-0.186*** (0.037)	-0.199*** (0.034)	-0.194*** (0.035)	-0.198*** (0.034)
Interaction (Treatment*female)	-0.076 (0.048)	-0.080 (0.053)	-0.082 (0.052)	-0.078 (0.050)	-0.058 (0.051)	-0.053 (0.050)
ITT female: Treatment + Interaction	-0.006	-0.012	-0.016	-0.005	0.000	-0.002
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	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
Female sibling engineer	No	No	No	No	No	Yes
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

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences. Sample is restricted to low ability students (first quartile of baseline math scores) in schools located in Piura, who answered the survey. 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 9: The Effect of Exposure to Role Models on students' career choices (low ability students) in Piura/Lambayeque/Tumbes schools

Dep. Variable:	Prefer Engineering					
Sample:	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* (0.035)	0.062 (0.038)	0.064* (0.038)	0.077** (0.036)	0.064* (0.036)	0.059 (0.036)
Female	-0.178*** (0.025)	-0.186*** (0.028)	-0.186*** (0.028)	-0.194*** (0.026)	-0.184*** (0.025)	-0.187*** (0.025)
Interaction (Treatment*female)	-0.078* (0.041)	-0.079* (0.043)	-0.083* (0.043)	-0.085** (0.042)	-0.073* (0.042)	-0.070* (0.041)
ITT female: Treatment + Interaction	-0.012	-0.017	-0.019	-0.008	-0.009	-0.012
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	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
Female sibling engineer	No	No	No	No	No	Yes
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

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences. Sample is restricted to low ability students (first quartile of baseline math scores) in schools located in Piura/Lambayeque/Tumbes, who answered the survey. 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 10: The Effect of Exposure to Role Models on students' career choices 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								
Quartile 1	0.076	-0.019	0.016	0.271	0.020	0.035	1437	0.333
Quartile 2	0.138	0.001	0.025	0.403	0.067	0.042	1558	0.174
Quartile 3	0.194	-0.002	0.039	0.546	-0.069	0.066	646	0.347
Quartile 4	0.205	0.091**	0.042	0.554	-0.002	0.049	939	0.121
Above median	0.200	0.046*	0.027	0.551	-0.017	0.037	1585	0.105
Below median	0.083	-0.004	0.017	0.302	0.046	0.034	2199	0.191
Panel B: Main Regions								
Quartile 1	0.068	-0.012	0.016	0.251	0.059	0.036	1132	0.093
Quartile 2	0.138	0.011	0.027	0.389	0.064	0.048	1246	0.329
Quartile 3	0.195	0.011	0.042	0.527	-0.008	0.072	515	0.821
Quartile 4	0.175	0.131***	0.044	0.573	-0.043	0.050	691	0.010
Above median	0.184	0.070**	0.027	0.558	-0.018	0.041	1206	0.056
Below median	0.077	0.003	0.017	0.276	0.070*	0.038	1737	0.119

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 11: The Effect of Exposure to Role Models on students' career choices 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								
Quartile 1	0.911	0.020	0.018	0.723	-0.032	0.037	1437	0.222
Quartile 2	0.850	0.001	0.027	0.583	-0.065	0.043	1558	0.187
Quartile 3	0.806	-0.009	0.040	0.445	0.063	0.065	646	0.319
Quartile 4	0.795	-0.097**	0.045	0.430	-0.013	0.043	939	0.135
Above median	0.800	-0.054*	0.028	0.435	0.005	0.037	1585	0.133
Below median	0.901	0.006	0.018	0.688	-0.056	0.036	2199	0.136
Panel B: Main Regions								
Quartile 1	0.915	0.017	0.018	0.741	-0.066*	0.039	1132	0.073
Quartile 2	0.847	-0.005	0.029	0.591	-0.051	0.049	1246	0.397
Quartile 3	0.805	-0.023	0.043	0.462	0.000	0.070	515	0.785
Quartile 4	0.825	-0.134***	0.046	0.416	0.020	0.045	691	0.017
Above median	0.816	-0.078***	0.028	0.431	0.001	0.043	1206	0.106
Below median	0.903	0.007	0.018	0.710	-0.072*	0.041	1737	0.095

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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: The Effect of Exposure to Role Models on students' perceptions by quartile of math performance

Outcome:	Control	Treatment	Standard	Control	Treatment	Standard	N	Diff (ITT)
Self-confidence	group mean	effect	error	group mean	effect	error		p-value
	female	(ITT)		male	(ITT)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full Sample								
Quartile 1	0.197	0.002	0.035	0.391	0.045	0.042	1509	0.383
Quartile 2	0.346	0.022	0.038	0.564	0.045	0.041	1612	0.635
Quartile 3	0.488	0.045	0.052	0.773	-0.062	0.069	658	0.205
Quartile 4	0.580	0.044	0.050	0.835	-0.090**	0.044	960	0.070
Above median	0.543	0.049	0.040	0.814	-0.068	0.042	1618	0.054
Below median	0.230	0.017	0.030	0.442	0.048	0.040	2297	0.453
Panel B: Main Regions								
Quartile 1	0.194	0.003	0.040	0.395	0.034	0.050	1190	0.588
Quartile 2	0.343	0.034	0.041	0.565	0.055	0.046	1290	0.710
Quartile 3	0.515	0.047	0.058	0.740	0.019	0.084	522	0.788
Quartile 4	0.551	0.125**	0.054	0.853	-0.116**	0.053	708	0.006
Above median	0.536	0.094**	0.044	0.814	-0.060	0.049	1230	0.035
Below median	0.224	0.024	0.035	0.450	0.038	0.045	1813	0.776

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' self-confidence in own math abilities to pursue engineering 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: The Effect of Exposure to Role Models on students' perceptions by quartile of math performance

Outcome:	Control	Treatment	Standard	Control	Treatment	Standard	N	Diff (ITT)
Male Successful	group mean	effect	error	group mean	effect	error		p-value
	female	(ITT)		male	(ITT)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full Sample								
Quartile 1	0.633	-0.037	0.040	0.391	-0.040	0.032	1400	0.951
Quartile 2	0.605	-0.050	0.039	0.564	0.011	0.029	1524	0.164
Quartile 3	0.629	0.017	0.050	0.773	-0.004	0.050	624	0.774
Quartile 4	0.557	-0.047	0.047	0.835	0.004	0.041	894	0.375
Above median	0.586	-0.015	0.033	0.814	-0.001	0.035	1518	0.755
Below median	0.637	-0.056*	0.032	0.442	-0.036	0.025	2135	0.612
Panel B: Main Regions								
Quartile 1	0.651	-0.061	0.044	0.395	-0.026	0.036	1126	0.565
Quartile 2	0.609	-0.045	0.043	0.565	-0.011	0.032	1233	0.473
Quartile 3	0.648	-0.007	0.056	0.740	-0.007	0.063	499	0.999
Quartile 4	0.567	-0.009	0.055	0.853	0.014	0.048	674	0.723
Above median	0.602	-0.006	0.039	0.814	-0.007	0.044	1173	0.992
Below median	0.664	-0.087**	0.035	0.450	-0.043	0.029	1715	0.306

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 14: The Effect of Exposure to Role Models on students' perceptions by quartile of math performance

Outcome: Engineering to Lorena	Control group mean	Treatment effect (ITT)	Standard error	Control group mean	Treatment effect (ITT)	Standard error	N	Diff (ITT) p-value
	female	female	(3)	male	male	(6)	(7)	(8)
	(1)	(2)		(4)	(5)			
Panel A: Full Sample								
Quartile 1	0.466	-0.046	0.042	0.516	-0.046	0.042	1473	0.997
Quartile 2	0.457	-0.001	0.042	0.508	0.054	0.037	1589	0.354
Quartile 3	0.535	0.048	0.057	0.579	-0.019	0.074	649	0.427
Quartile 4	0.579	0.005	0.042	0.527	0.040	0.051	941	0.588
Above median	0.561	0.025	0.034	0.545	0.024	0.042	1590	0.981
Below median	0.462	-0.041	0.034	0.523	-0.038	0.037	2249	0.944
Panel B: Main Regions								
Quartile 1	0.464	-0.035	0.049	0.492	-0.039	0.050	1172	0.940
Quartile 2	0.448	0.003	0.047	0.479	0.086*	0.044	1270	0.235
Quartile 3	0.515	0.039	0.066	0.552	-0.006	0.092	520	0.644
Quartile 4	0.589	-0.026	0.050	0.520	0.057	0.049	697	0.205
Above median	0.557	0.016	0.041	0.531	0.047	0.048	1217	0.520
Below median	0.448	-0.030	0.039	0.496	-0.021	0.043	1784	0.848

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 15: The Effect of Exposure to Role Models on students' perceptions by quartile of math performance

Outcome:	Control	Treatment	Standard	Control	Treatment	Standard	N	Diff (ITT)
Types of engineering listed	group mean	effect	error	group mean	effect	error		p-value
	female	(ITT)		male	(ITT)			
	(1)	female	(3)	male	(5)	(6)	(7)	(8)
	(2)							
Panel A: Full Sample								
Quartile 1	4.348	-0.075	0.085	4.177	-0.097	0.088	1518	0.847
Quartile 2	4.334	-0.055	0.080	4.330	0.026	0.069	1621	0.396
Quartile 3	4.502	0.032	0.089	4.484	0.085	0.119	661	0.698
Quartile 4	4.610	-0.096	0.070	4.526	0.040	0.088	963	0.163
Above median	4.567	-0.042	0.060	4.512	0.075	0.066	1624	0.148
Below median	4.326	-0.093	0.076	4.212	-0.065	0.066	2309	0.754
Panel B: Main Regions								
Quartile 1	4.324	-0.035	0.098	4.205	-0.142	0.094	1198	0.379
Quartile 2	4.334	-0.004	0.085	4.346	0.030	0.077	1296	0.763
Quartile 3	4.515	0.018	0.092	4.458	0.157	0.146	525	0.379
Quartile 4	4.654	-0.203**	0.077	4.565	0.005	0.083	710	0.063
Above median	4.594	-0.098	0.067	4.529	0.106	0.068	1235	0.024
Below median	4.307	-0.053	0.085	4.219	-0.053	0.067	1824	0.999

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' number of engineering types 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 16: The Effect of Exposure to Role Models on students' perceptions by quartile of math performance

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								
Quartile 1	8.196	-0.056	0.041	8.168	-0.003	0.044	1499	0.353
Quartile 2	8.194	-0.032	0.037	8.182	0.051	0.037	1613	0.072
Quartile 3	8.154	-0.007	0.043	8.239	-0.087	0.054	655	0.201
Quartile 4	8.235	-0.007	0.052	8.230	-0.056	0.043	953	0.465
Above median	8.202	0.005	0.035	8.233	-0.062*	0.033	1608	0.147
Below median	8.191	-0.059*	0.031	8.173	0.017	0.033	2284	0.091
Panel B: Main Regions								
Quartile 1	8.199	-0.064	0.045	8.168	0.022	0.050	1187	0.201
Quartile 2	8.188	0.002	0.038	8.176	0.095**	0.041	1291	0.061
Quartile 3	8.168	-0.008	0.047	8.244	-0.090	0.068	523	0.270
Quartile 4	8.226	0.007	0.062	8.266	-0.078	0.052	707	0.249
Above median	8.201	0.016	0.040	8.258	-0.077*	0.041	1230	0.083
Below median	8.190	-0.046	0.035	8.167	0.051	0.035	1810	0.056

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' number of engineering types 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix

Figure A1: Thumbnails of Slides Shown During School Visits



Figure A2: Thumbnails of Slides Shown During School Visits



Table A1: Effect on students' preference for Engineering: Including covariates

Sample:	(1) Full	(2) 4Q	(3) AM	(4) BM	(5) 1Q	(6) 4Q3R
Treatment	0.0179 (0.0237)	-0.00162 (0.0489)	-0.0170 (0.0367)	0.0416 (0.0285)	0.0196 (0.0355)	-0.0430 (0.0501)
Interaction (Treatment*female)	-0.00797 (0.0269)	0.0928 (0.0593)	0.0628 (0.0384)	-0.0504 (0.0328)	-0.0387 (0.0398)	0.174*** (0.0651)
Female	-0.261*** (0.0184)	-0.307*** (0.0385)	-0.321*** (0.0310)	-0.226*** (0.0224)	-0.195*** (0.0251)	-0.354*** (0.0422)
own_house	0.0311* (0.0164)	0.0734 (0.0482)	0.0571* (0.0328)	0.0168 (0.0169)	-0.00729 (0.0260)	0.0709 (0.0581)
mother_engineer	0.0364 (0.0290)	0.0407 (0.0987)	0.0384 (0.0555)	0.0277 (0.0334)	0.0227 (0.0456)	0.0372 (0.126)
father_engineer	0.0412** (0.0202)	0.0876* (0.0442)	0.0609* (0.0336)	0.0239 (0.0238)	0.00108 (0.0284)	0.0941 (0.0623)
age	-0.0357*** (0.0124)	-0.000528 (0.0398)	-0.0200 (0.0235)	-0.0422** (0.0175)	-0.0139 (0.0196)	-0.00987 (0.0465)
female_sibling_in_ENG	0.0635** (0.0246)	0.167*** (0.0601)	0.0728 (0.0460)	0.0538 (0.0329)	0.0370 (0.0423)	0.218*** (0.0586)
Math	0.0510*** (0.00383)	0.0290 (0.0207)	0.0372** (0.0147)	0.0490*** (0.00536)	0.0277*** (0.00922)	0.0287 (0.0229)
Language	-0.0235*** (0.00638)	-0.0328*** (0.0120)	-0.0294*** (0.0110)	-0.0206*** (0.00504)	-0.0215*** (0.00593)	-0.0200 (0.0143)
Science	-0.00507 (0.00554)	-0.00310 (0.0114)	-0.0105 (0.00999)	-0.00350 (0.00567)	-0.00640 (0.00569)	-0.00208 (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 intent to treat (ITT) estimates of the role model interventions on grade 11 students' preferences for engineering, including the estimates on covariates, separately for the different subgroups of students. The estimates are obtained from a regression of our main outcome following equation (1). 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 A2: The Effect of Exposure to Role Models on students' career choices by quartile of math performance: LATE

Outcome: Prefer Engineering	Control group mean	Treatment effect (LATE)	Standard error	Control group mean	Treatment effect (LATE)	Standard error	N	Diff (LATE) p-value
	female	female	(3)	male	male	(6)	(7)	(8)
	(1)	(2)		(4)	(5)			
Panel A: Full Sample								
Quartile 1	0.076	-0.020	0.017	0.271	0.021	0.038	1437	0.333
Quartile 2	0.138	0.001	0.027	0.403	0.071	0.044	1558	0.174
Quartile 3	0.194	-0.002	0.042	0.546	-0.073	0.070	646	0.347
Quartile 4	0.205	0.097**	0.045	0.554	-0.002	0.052	939	0.121
Above median	0.200	0.049*	0.029	0.551	-0.018	0.039	1585	0.105
Below median	0.083	-0.004	0.018	0.302	0.049	0.036	2199	0.191
Panel B: Main Regions								
Quartile 1	0.068	-0.012	0.017	0.251	0.062	0.038	1132	0.093
Quartile 2	0.138	0.012	0.029	0.389	0.068	0.051	1246	0.329
Quartile 3	0.195	0.012	0.045	0.527	-0.008	0.076	515	0.821
Quartile 4	0.175	0.139***	0.046	0.573	-0.046	0.053	691	0.010
Above median	0.184	0.074**	0.028	0.558	-0.019	0.044	1206	0.056
Below median	0.077	0.003	0.018	0.276	0.075*	0.041	1737	0.119

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 A3: Robustness Check: High-ability Math and Science

Outcome:	Control	Treatment	Standard	Control	Treatment	Standard	N	Diff (ITT)
Prefer Engineering	group mean	effect	error	group mean	effect	error		p-value
	female	(ITT)		male	(ITT)			
	(1)	female	(3)	(4)	male	(6)	(7)	(8)
	(2)			(5)				
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
Above median M & S	0.206	0.032	0.030	0.537	0.029	0.043	1242	0.958
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
Above median M & S	0.194	0.064**	0.031	0.544	0.024	0.049	932	0.468

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 A4: Robustness Check: Average school ECE math scores

Outcome: Prefer Engineering	Control group mean	Treatment effect (ITT)	Standard error	Control group mean	Treatment effect (ITT)	Standard error	N	Diff (ITT) p-value
	female	female		male	male			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All	0.139	-0.002	0.020	0.405	0.007	0.025	4229	0.762
Quartile 1	0.076	-0.035*	0.019	0.271	0.019	0.037	1325	0.173
Quartile 2	0.138	0.000	0.032	0.403	0.057	0.044	1455	0.273
Quartile 3	0.194	-0.009	0.046	0.546	-0.067	0.066	598	0.426
Quartile 4	0.205	0.057	0.042	0.554	-0.038	0.057	851	0.132
Above median	0.200	0.025	0.030	0.551	-0.043	0.039	1449	0.094
Below median	0.083	-0.030	0.020	0.302	0.030	0.034	2049	0.133
Main Regions								
3 Regions (3R)	0.129	0.014	0.022	0.396	0.029	0.027	3678	0.676
Quartile 1	0.068	-0.029	0.019	0.251	0.050	0.039	1036	0.070
Quartile 2	0.138	0.007	0.036	0.389	0.054	0.049	1155	0.428
Quartile 3	0.195	-0.015	0.052	0.527	-0.042	0.073	473	0.751
Quartile 4	0.175	0.095**	0.037	0.573	-0.092	0.057	621	0.007
Above median	0.184	0.038	0.028	0.558	-0.063	0.040	1094	0.029
Below median	0.077	-0.026	0.022	0.276	0.049	0.038	1609	0.105

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 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 A5: Treatment effect by distance between role model's high school and visited school

Plan to Study Engineering					
Treatment effect (ITT)					
	Full sample (1)	Girls (2)	Boys (3)	Girls in 3 regions (4)	Boys in 3 regions
Less than 4 km distance	0.056 (0.034)	0.016 (0.035)	0.004 (0.053)	0.016 (0.035)	0.004 (0.054)
Less than 2km distance	0.039 (0.040)	0.049 (0.033)	-0.018 (0.052)	0.049 (0.033)	-0.018 (0.052)
Less than 1 km distance	0.084** (0.035)	0.090* (0.046)	-0.011 (0.052)	0.090* (0.046)	-0.011 (0.052)
N	4363	2412	1935	1924	1470

Notes: This table reports the treatment effects estimates (ITT) on a dependent variable that equals one if the student plans to study engineering and zero otherwise, separately for different groups of students, and by distance (in km) between the role model's high school and the school she visited. 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 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 (Treatment*distanceAMUDEP)	-0.142* (0.0747)	-0.161** (0.0748)	-0.156** (0.0745)	-0.162** (0.0774)	-0.167** (0.0802)	-0.167** (0.0810)
distanceAMUDEP	0.119 (0.101)	0.109 (0.115)	0.109 (0.114)	0.192 (0.120)	0.181 (0.125)	0.181 (0.125)
Treatment ITT near schools	0.148*** (0.0491)	0.168*** (0.0481)	0.162*** (0.0484)	0.170*** (0.0527)	0.172*** (0.0568)	0.172*** (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	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
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 (Treatment*distanceAMUDEP)	-0.133** (0.0649)	-0.120 (0.0733)	-0.117 (0.0742)	-0.132* (0.0714)	-0.138** (0.0674)	-0.128* (0.0694)
distanceAMUDEP	-0.0239 (0.0978)	-0.0864 (0.0873)	-0.0882 (0.0878)	-0.0202 (0.0850)	0.0331 (0.0811)	0.133 (0.0857)
Treatment ITT near schools	0.111** (0.0463)	0.101* (0.0521)	0.101* (0.0519)	0.114** (0.0481)	0.0872* (0.0473)	0.0793* (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	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
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, 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	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
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 (Treatment*distanceAMUDEP)	-0.0757*** (0.0274)	-0.0734** (0.0280)	-0.0744*** (0.0279)	-0.0759*** (0.0278)	-0.0516* (0.0307)	-0.0419 (0.0307)
distanceAMUDEP	-0.0145 (0.0491)	-0.0369 (0.0509)	-0.0426 (0.0499)	-0.00704 (0.0531)	-0.000503 (0.0590)	-0.00206 (0.0556)
Treatment ITT near schools	0.0406** (0.0172)	0.0385** (0.0176)	0.0390** (0.0172)	0.0394** (0.0178)	0.0297* (0.0176)	0.0266 (0.0175)
Treatment + uddistreat ITT far schools	-0.035	-0.035	-0.035	-0.037*	-0.022	-0.015
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	No	No	No	Yes	Yes	Yes
Baseline Scores	No	No	No	No	Yes	Yes
Student's age	No	No	No	No	No	Yes
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

VARIABLES	(1) 4Q3R	(2) AM	(3) AM3R	(4) BM	(5) BM3R
uddistreat (Treatment*distanceAMUDEP)	-0.132 (0.0862)	-0.0965* (0.0520)	-0.0785 (0.0557)	-0.0146 (0.0297)	0.0171 (0.0416)
distanceAMUDEP	-0.920*** (0.0922)	0.247** (0.0958)	-0.510*** (0.0411)	-0.0720 (0.0634)	-0.182*** (0.0157)
Treatment ITT near schools	0.173*** (0.0545)	0.0904*** (0.0324)	0.0925*** (0.0325)	-0.00343 (0.0136)	-0.00375 (0.0141)
Treatment + uddistreat ITT far schools	0.041	-0.006	0.014	-0.018	0.013
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. Covariates include baseline scores, student's age, mother or father engineer, ownership of house, parental education fixed effects, and an indicator for 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

VARIABLES	(1) 1Q3R	(2) AM	(3) AM3R	(4) BM	(5) BM3R
uddistreat (Treatment*distanceAMUDEP)	-0.0479 (0.0664)	-0.0949 (0.0713)	-0.131 (0.0933)	-0.0894 (0.0591)	-0.113* (0.0659)
distanceAMUDEP	0.430*** (0.0985)	-0.149** (0.0627)	-0.165*** (0.0427)	0.0333 (0.0998)	-0.0648** (0.0253)
Treatment ITT near schools	0.0784 (0.0474)	0.0390 (0.0469)	0.0383 (0.0487)	0.0880** (0.0439)	0.0880** (0.0438)
Treatment + uddistreat ITT far schools	0.030	-0.056	-0.092	-0.001	-0.025
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. Covariates include baseline scores, student's age, mother or father engineer, ownership of house, parental education fixed effects, and an indicator for 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: Preferences for Engineering: Only Girls

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

Notes: This table reports the treatment effects estimates on girls' preferences for Engineering by type, 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: The Effect of Exposure to Role Models on students' career choices by quartile of math performance

Outcome:	Control	Treatment	Standard	Control	Treatment	Standard	N	Diff (ITT)
Any three types of engineering	group mean	effect	error	group mean	effect	error		p-value
	female	(ITT)		male	(ITT)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full Sample								
Quartile 1	0.042	-0.006	0.015	0.220	0.013	0.036	1437	0.635
Quartile 2	0.101	0.012	0.023	0.321	0.046	0.038	1558	0.443
Quartile 3	0.146	0.015	0.032	0.496	-0.064	0.061	646	0.225
Quartile 4	0.142	0.104**	0.040	0.512	-0.030	0.048	939	0.019
Above median	0.143	0.061**	0.026	0.507	-0.037	0.036	1585	0.010
Below median	0.052	0.002	0.015	0.246	0.018	0.030	2199	0.596
Panel B: Main Regions								
Quartile 1	0.034	0.000	0.016	0.202	0.051	0.038	1132	0.224
Quartile 2	0.104	0.023	0.025	0.306	0.052	0.042	1246	0.559
Quartile 3	0.152	0.018	0.034	0.484	-0.011	0.073	515	0.725
Quartile 4	0.132	0.134***	0.041	0.534	-0.074	0.048	691	0.001
Above median	0.141	0.074***	0.027	0.517	-0.041	0.042	1206	0.010
Below median	0.048	0.007	0.016	0.227	0.036	0.035	1737	0.422

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for engineering programs 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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? 0 1 2 3 4 5 ≥ 6

Q26. How many brothers do you have in total? 0 1 2 3 4 5 ≥ 6

Q27. How many sisters do you have in total? 0 1 2 3 4 5 ≥ 6

Q28. How many of your brothers are currently studying at university?

0 1 2 3 4 5 ≥ 6

Q29. How many of your sisters are currently studying at university? 0 1 2 3 4 5 ≥ 6

Q30. How many of your brothers are currently studying engineering?

0 1 2 3 4 5 ≥ 6

Q31. How many of your sisters are currently studying engineering?

0 1 2 3 4 5 ≥ 6

Q32. How many of your brothers are engineers?

0 1 2 3 4 5 ≥ 6

Q33. How many of your sisters are engineers?

0 1 2 3 4 5 ≥ 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? 1 2 3 4 ≥ 5

2. No

Q36. Is there a motorcycle in your home? :

1. Yes → How many? 1 2 3 4 ≥ 5

2. No

Q37. Is there a TV in your home? :

1. Yes → How many? 1 2 3 4 ≥ 5

2. No

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

1. Yes → How many? 1 2 3 4 ≥ 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!