Creating future female scientists: Experimental evidence on improving STEM skills and attitudes in Peru

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PRELIMINARY DRAFT

Abstract

The STEM gender gap has strongly persisted over the years and it is even more pronounced in developing countries. We study the case of a program that provides weekly science workshops to young girls in Lima, Peru. We evaluate whether this program improves girls' educational achievement, attitudes and aspirations using an experimental design. We find no significant effects on girls' academic performance until after 2 years of the program. However, we find that girls who participated in the program are more overconfident about their grades in science, have strong negative perceptions of non-STEM majors, and trade-off school time for personal projects.

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1 Introduction

Over the past 30 years, the gender gap of educational attainment has been reduced in many developed countries and more recently in developing ones (Bailey and Dynarski, 2011; Rosenzweig and Zhang, 2013). Nonetheless, the gender gap in science, technology, engineering and mathematics (STEM) education and careers strongly persists (Ellison and Swanson, 2010; Cheryan et al., 2015; Gonzalez De San Roman and De La Rica, 2016; Eble and Hu, 2019a) and it is even more pronounced in developing countries (Jayachandran, 2015). For example, in Africa and Latin America, the gender gap in mathematics achievement tends to favor boys as early as end of primary school (UNESCO, 2017). Therefore, many countries seek to address the lower participation and learning achievement of girls in STEM education. In this paper, we examine whether a weekly workshop out-of-school intervention in primary school years can improve girls STEM skills, aspirations and attitudes.

Recent literature has shown that gender gaps in STEM are not the result of biological factors or innate ability (Kersey). Rather, evidence suggests that girls' and women's participation, achievement and progression in STEM studies and careers are driven by multiple and overlapping factors. Among these, the more salient are: gender stereotypes, role models, and cultural norms that influence parental and teachers beliefs as well as expectations (Eble and Hu, 2019a; UNESCO, 2017; Frome and Eccles, 1998) among others. We study the case of MacTec, an educational program in Lima, Peru. Each year since 2016, they randomly choose 40 girls between ages 8 and 11, who participate in a one-year program consisting of weekly workshops with top American and Peruvian scientists. This is a unique intervention as it targets girls in primary school at a critical period before gaps in STEM abilities widen. The goal of these workshops was to promote girls' discovery of nature and science while exposing them to successful women in STEM careers. In this setting, we aim to study how exposure to high-profile role models in STEM (university professors from Peru and the US) during primary school improve girls human capital, aspirations, and attitudes?

We address our research question using experimental evidence. Conditional on applying, the program selects participants using a lottery which provides the setting of a randomized control trial. We analyze the 2016-2019 program cohorts by matching 2016-2019 applicants ($\sim$ 2,800 girls) to administrative school records (centralized system that records enrollment, grades by subject). We also conduct an endline survey to measure attitudes, beliefs and aspirations. Our empirical strategy leverages the lottery assignment of applicants by comparing post outcomes between participants versus non-participants conditional on applying. We also analyze the sample of girls applying to the program and we find high selection compared to the average population of girls in that age. Using administrative school data, we find that girls who applied to the program attend better schools and using data from the 2019 application data, we find that applicants' parents have significant more years of education compared with the population. Nevertheless, we are able to corroborate the validity of the randomization. The baseline socio-demographic and educational characteristics (before the intervention) are balanced between selected (treated) and non-selected (control) applicants, which validates our empirical strategy.

Our results suggest that this program had no significant effects on academic achievement measured with school grades, even 2 years after the program. However, our endline results show that girls who participated in the program are more confident about their science grades at school. What is more, when contrasting their perceptions about their performance with real data, we find that they are more overconfident that the control group. However, we do not find significant effects on their perceptions about ability and effort. In particular, the signs for the impacts in efforts are negative and they are consistent with the effects on time use. Girls in the treatment group also report spending less time on studying and school homework. Instead, they report spending more time on personal projects. This suggests that they might be trading off school related time with personal development activities. What is more, these patterns of results of less effort at school might be a sign of higher productivity.

Regarding expectations and aspirations about their future, we asked girls some questions about aspirations for education and occupation; and we aggregate responses into an aspirations index. However, we did not find evidence that participation in the program changed those measures of aspirations, but we do highlight that these expectations were already high in the baseline collected in 2019. In addition, we asked girls about their perceived happiness if they were to study a list of different STEM and Non-STEM majors. We find that treated girls seem have more pessimistic perceptions of happiness about any major in college but the effects are stronger for non-STEM majors, specially Law, Education and Journalism. They also seem to be also very pessimistic about Mathematics and Architecture majors, which are STEM-related majors that are not covered in the workshops of the program. When it comes to major choice, we also do not find significant effects on STEM related majors. We believe that since girls who applied to the program were already interested in STEM, it could be the case that they just kept their already high initial level interest. We confirm this hypothesis with some questions regarding social norms, where we do not find effects on attitudes towards marriage and lady-like careers. However, we do find that girls who participated in the program seem to be less likely to follow family advice and to talk to parents about their educational future. Finally, it is worth noting that since the endline was implemented during the COVID-19 pandemic, we also explore girls' mental health status. Even when the coefficients are not significant, we find signs that girls in the treatment group might be experiencing stress and frustration than those who do not participated in the program.

The next section will discuss the literature related to our research question. Section 3 will describe the program and the intervention we are studying and it will also run an analysis of selection. Section 4 presents the experimental design and the validation of the randomization. Section 5 presents the results using administrative data and our endline survey and Section 6 concludes with some discussion of our results.

2 Literature Review

This project contributes to several literatures. First, the program provides a unique intervention as it targets girls during primary school at ages 8 to 11, while most of similar interventions focus on older students. This is an important feature since earlier interventions could potentially have bigger impacts and this one is implemented at a critical period before gaps in STEM abilities widen up (UNESCO, 2017). So far, the literature has provide strong evidence on secondary or college women (Del Carpio and Guadalupe (2018); Moss-Racusin et al. (2018); Porter and Serra (2020); Dennehy and Dasgupta (2017)). However, a growing body of evidence suggests that early interventions to this demographic group can be very effective as attitudes and soft skills are being formed and are, therefore, malleable (Heckman and Rubinstein, 2001; Bandiera et al., 2020; Alan and Ertac, 2018; Dhar et al., 2018, 2015). We will complement this literature by providing evidence of effects of an after-school intervention on science education targeting girls before they initiate adolescence in a large urban setting in a developing country.

Second, we study a novel intervention based on role models. The closest work to ours is Breda et al. (2020), which finds that one-hour visit of a female role model with a background in science has an impact on students' choice of field of study after high school graduation, particularly for high-achieving females. They also find that an increase in the probability that a female student would enroll in a male-dominated STEM track in college. Unlike them, we focus on very young girls in primary school and study effects of whole year program in a developing country where the gender gap is even wider. Some other studies have shown positive effects of the role of female teachers on girls' academic achievement (e.g.,Eble and Hu (2019b)) and enrollment in STEM majors (e.g, Carrell et al. (2010)). Moreover, Carlana (2019), using gender-science implicit association tests, finds that teachers with stronger implicit stereotypes negatively affect math achievements of their female students. Thus, female teachers may also be affecting students' outcomes by exposing them to different gender stereotypes. In addition, there is evidence that interventions involving educational or professional role models can improve children outcomes Porter and Serra (2020); Dennehy and

Dasgupta (2017); Kearney and Levine (2020); Beaman et al. (2012); Tanguy et al. (2014). We complement this literature by studying the role of being exposed to top scientists leaders that are external to the classroom during a full academic year. Even when we are not able to disentangle the differential effects, this program provides top role models (i.e a university professor in the US) and local role models (i.e Peruvian girl majoring in science in a local university). What is more, around 50 percent of the top scientists mentors are female which reflects the program efforts to have parity even when in reality it is hard to find top female scientists in Peru. Thus, we believe that the intervention can potentially be scale up with an the increasing the number of female teachers in the classroom given the low number of female STEM related teachers in developing countries. As a further matter, in recent decades there has been a decline in the number of women becoming teachers.

Third, a large body of research studied how aspirations and beliefs are formed and their effect on human capital investments (Tanguy et al., 2014; Akerlof and Kranton, 2000; Benabou and Tirole, 2011; Lybbert and Wydick, 2016). For example, it has been documented that a lack of math self-efficacy drives women's drop out from STEM majors Saltiel (2021). We complement this work by showing how external role models can affect these outcomes for girls at a critical period for human capital formation. In particular, we study how exposure to top scientists can affect girls' aspirations and beliefs and how this may translate on investment in skills, and academic performance.

3 Context

3.1 Description of the Intervention

Founded on 2012, MacTec Peru [1] is an NGO that seeks to eradicate scientific illiteracy in Peru. Each year, they randomly choose 40 girls for a one-year program where they participate in weekly workshops with American and Peruvian top scientists. Also, after the workshops, participants work in small groups under the mentoring of a big-sister fellow[2], following the *Discovery Peer Learning* Method. This method is quite different from traditional classes: participants are invited to work along with the lecturer (who acts more like a leader than a teacher). During these workshops, creativity and critical thinking are strongly encouraged with constant debate and questioning. Additionally, no rankings or test scores are used on the workshops and since this is not a remedial program, they do not follow or include topics from the Ministry of Education's curricula. Most of the topics covered in class are university

[1] For more information about this NGO, visit their official website.

[2] This fellow is usually a Peruvian college STEM female student who works leading a group of 5 girls during the whole year.

level topics that are simplified for young students. For example, optics, DNA extraction or crystallization processes.

The program was implemented in Lima, Peru's capital and a city of approximately 12 million people. The Peruvian context, similar to any other Latin American country, shows a very rough scenario for women. The gender gap on salaries is 30 %. Even for highly educated women in STEM (with BA), the wage gender gap is 23%. However, the adversities for women do not come exclusively from earnings: a lot of the barriers and difficulties are cultural. Lima is considered one of the worst cities in the world for women, comparable to New Dheli and Kampala.[3] As documented by Sviatschi and Trako (2021), Peru is a country that has experienced a huge increment of gender violence, where the number of domestic violence cases registered in local police departments has increased substantially: from 29,759 in 2002 to more than 60,000 in 2016. At the same time, numerous political and religious groups have emerged claiming their opposition to the *'gender ideology'* and the implementation of a school curricula that includes a gender equality agenda [4].

In this context, MacTec has pushed their agenda for gender equality in STEM, providing a safe and friendly environment for girls to demonstrate their curiosity and creativity for science topics. We interviewed the program staff, and they shared with us their difficulties when it comes to recruiting volunteer staff and fellows. Even when they have aimed to reach a more diverse audience, and to expand it outside the city of Lima, there is still several barriers to reach girls at the bottom of the distribution. However, the program has had an increasing demand over the years. Anecdotally, they mentioned that elite schools in Lima have often asked them to implement the program and to pay for it but they were not able to expand it due to the high cost of the implementation. The average cost of one scholarship is 2,000 USD per year, compared with the average government expenditure of approximately 1,000 USD per year in primary school.

The program runs every year following the timeline showed on Figure 1. It starts during the Peruvian summer break (January-March) with the application season. They advertise mainly on social media during the summer break and implement school visits in March, when the school year starts. The online applications are open until the last day of March, and the lottery is run the day after in a public ceremony. All workshop activities are held

[3] Plan International has documented experiences on cities across the world, where Lima came out as one of the worst cities in the world for women. See report here.

[4] #ConMisHijosNoTeMetas is an active social movement and it has spread to other countries like Colombia, Chile and Spain. Their main claim is that the Government shouldn't teach children about gender and sexual orientation, since this choice belongs to the parents. Their flag is blue and pink, symbolizing the color of masculine and feminine genders.

every Saturday ($\sim 4 hours$ per session), from April to November, except during the national holidays or the Peruvian winter break (July). Parents of selected participants are ask to sign an agreement where they commit to attend every workshop and they are aware that after 3 unjustified missing classes, the students are invited to retire from the program. On average, one girl per year drops out the program within the first weeks. If she dropped out during the first 3 weeks, she is replaced with another girl that was randomly assigned as well. We study all girls who finish the program at the end of the academic year.

Figure 1: Official Timeline of the Program

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Application Season			Workshops Season								Summer Break
Draw on April 1st			*Meeting every Saturday Morning, except holidays*								

3.2 Selection

In this subsection, we examine selection into applying to the program. First, we take a look at the characteristic of the pool of applicants from 2016-2019. Approximately, 85% of them are from the main Lima Metropolitan area.[5]. The average applicant age is 9.4 for a range of 8-11 years old. They mostly come from north and east side of Lima, as seen in Figure A.22. These districts are the most populated areas and usually with high concentration of low and middle SES families. Around 20 % of the applicants come from public schools and 9% come from only-girls schools. The low amount of applicants coming from public schools might suggest a bias towards richer households, however, the Peruvian context is quite different. Approximately 50% of students are enrolled in private schools in Lima, and there is a lot of variation across prices. As in many developing countries, rates of privatization are larger in urban areas. In Lima, the share of private schools increased from 23% in 2000 to 51% in 2017 (Allende, 2020).

Next, we study if there is selection on who applies to the program. We use public available data from all primary schools in Lima and compare them with the schools where these applicants come from. We use information about the schools' neighborhood and we measure the percentage of poverty surrounding the school and private school fees as a proxy for families' socio-economical background. As seen in Figure A.21, there are no systematical differences between applicants' schools and the universe of schools in Lima. This can suggest that in terms of socioeconomic background, our sample is representative on average from the population, with most applicants are coming from middle class neighborhoods, as suggested

[5]Anecdotally, the program director informed that they constantly have requests from different regions to implement the program outside Lima. Some parents outside the City applied hoping to get the scholarship and plan to move or commute to the city during the weekends.

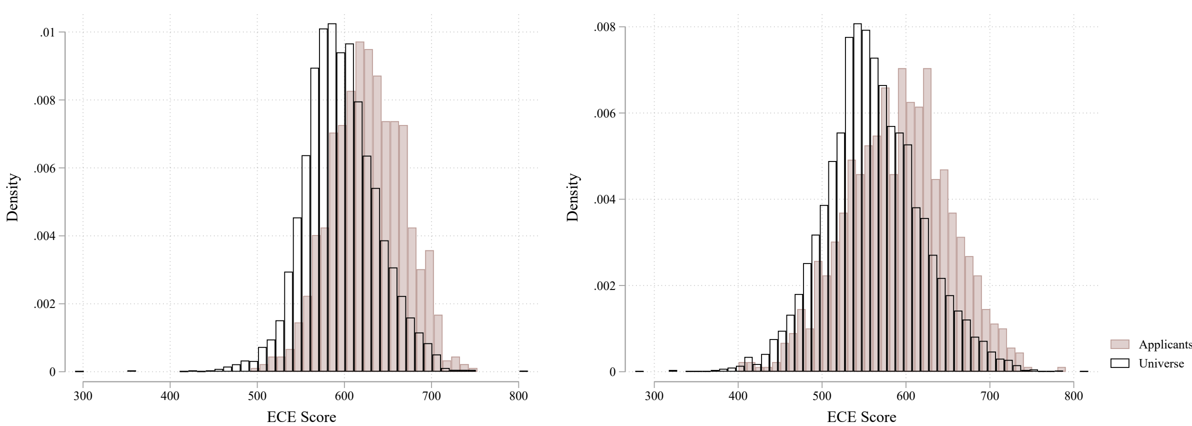
before or more importantly, most applicants' schools are in neighborhoods with a low share of poor households as defined by the governments records. Applicants coming from private schools pay approximately 100 USD per month in school fees, which is consistent with one third of the Peru's minimum monthly wage.

Additionally, we compare the results of ECE (*Examen Censal de Estudiantes*), the national standardized test for second graders in Figure 2. Most applicants come from schools with significantly higher performance on these tests, both in Mathematics and Spanish. This suggests that applicants do come from better schools, implying that parents invest more on their education, regardless of their economics status. Overall, we can see that there is selection on who applies to the program with a clear profile: applicants come from families that are from middle class and attend schools with better education performance than their national peers. In addition, during the 2019 application period, we collected a baseline survey and we confirmed that most of the applicants' parents have a college degree or more. More details are described on Appendix A.

Figure 2: School Average on National Standardized Test for 2nd graders

(a) Spanish

(b) Mathematics

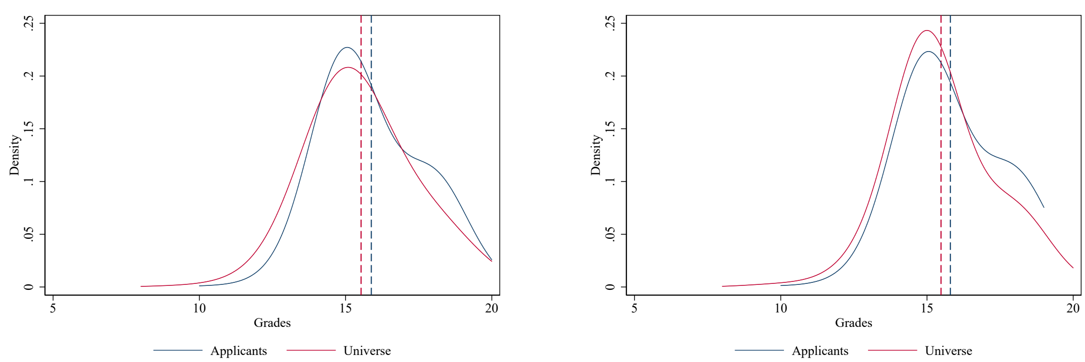


To understand some of our academic achievement results, it is important to see the relative ranking of the applicant with their school cohort. Using the matched data with the administrative records (as detailed on the following section), we compare the pool of applicants with students in their same class the year before applying to the program. In Figure 3 we can see that applicants to the program have a higher grades in STEM courses the distribution of applicants seem to be bi-modal, where there is a group of girls having significantly higher grades. The results are quite similar when looking at non-STEM courses as seen on Figure A.23. We pay a special look at this since it shows how much room these girls have to improve their grades and as we can see, given that these girls were already good students, they had limited space to improve their academic performance.[6]

Figure 3: Selection in School STEM Subjects Performance

(a) Science

(b) Mathematics



3.3 Data

First, we use administrative data with student's records including grades for multiple subjects from 2014 to 2020. Given that is was impossible to implement a name-to-name match with the official records because of the Peruvian Law that protects personal information, we use the following procedure. We got access to all students records with sex, birthday and school codes. On the other side, from the program records, we also have the same variables. Given that the likelihood of having the same sex and birthday in the same school is quite small, we assume that most matches are correct, nevertheless we only considered the cases the probability of matching is 100 percent. We were able to match approximately 70 percent of our sample.

Second, we implemented an online survey during the summer of 2020. We collected an online survey targeting all previous families who applied to program since 2016. This survey was conducted during the COVID-19 outbreak that was continuously exacerbating while Lima was in a strict lockdown. The city was particularly vulnerable because of its high density and the lack of a health system ready to face the pandemic. This situation made the survey harder to implement and we acknowledge that our results should be taken carefully given this unique situation. We designed an online friendly questionnaire to collect data where families were able to fill the survey in a desktop, laptop, smartphone or tablet. They

[6]For all of these grade distributions, we have that their Kolmogorov-Smirnov test rejects the equality of the two distributions with $pvalue \leq 0.001$.

were reached via e-mail, text messages and phone calls and our response rate was 20 percent approximately, a regular rate when it comes to online surveys. We collected information on 350 families during a month. The survey included two sections: one exclusively for parents and another one exclusively for applicants.[7] The survey sample was randomly selected from program's administrative records, a pool of approximately 2000 applicants from 2016 to 2019. Families from older cohorts were harder to reach: phones and emails were not updated or they may have forgotten about their application to the program and refused to fill the survey. Sample selection was stratified by application year and Table 12 shows the balance between treatment and control in this sample. [8]

Additionally, we also use public available data of schools. We are able to match all applicants to the their schools in the year they applied to the program. We use this data for the randomization validation and selection analysis.

4 Experimental Design

4.1 Randomization

Every year, the program randomly selects new scholars in a lottery that is transmitted live, usually on social media. After being selected, parents have a few days to accept the scholarship. They have to sign a commitment where they commit to bring their kid every Saturday for the weekly workshop. After 3 unjustified missed class, they are removed from the program. There were only a few anecdotal cases where people rejected the scholarship and they were automatically replaced with another randomly selected applicant before the program starts. We find that conditional on applying, there are no systematic differences between applicants who obtained the scholarship (also called treated) and those who did not as seen on Table 1. What is more, by looking at the geographical distribution of applicants on Figure 4 (GPS location of their address at application time), treated applicants households are similarly dispersed around the city than their control counterparts.

Using the same measures as in the previous section (the percentage of extremely poor households around 3km of school enrolled), treated and control students are quite similar in terms of their neighborhood poverty distribution as well as in their private school fees, as seen in Figure A.24. Additionally, we do not find significant differences on the quality of schools attended by treated and control applicants as measured by average test scores for 2nd

[7]We were not able to make sure parents did not intervened when girls responded their part of the survey. However, we constantly reminded them that they should leave girls to answer on their own. Results from survey show that they indeed answered differently.

[8]Table 12 shows the balance controlled by year of application.

Table 1: Balance Control and Treatment

Variable	(1) Control	(2) Treatment	(3) Difference
Age	9.465	9.456	-0.009
	(1.253)	(1.036)	(0.101)
Grade	4.486	4.419	-0.067
	(1.325)	(1.200)	(0.108)
Public	0.194	0.196	0.002
	(0.396)	(0.398)	(0.033)
Poverty Around School	0.159	0.146	-0.013
	(0.132)	(0.116)	(0.011)
School Fee (PEN)	677.720	721.040	43.320
	(543.697)	(583.855)	(50.213)
ECE Spanish	645.948	643.990	-1.958
	(42.705)	(41.101)	(3.601)
ECE Math	611.644	608.382	-3.262
	(58.492)	(56.052)	(4.931)
No. Teachers	22.233	24.171	1.938
	(15.387)	(17.773)	(1.276)
No. Students	412.585	428.544	15.959
	(295.707)	(339.738)	(24.513)
Observations	2,529	160	2,691

graders, both for mathematics and Spanish, as seen on Figure 5. All this evidence suggests that conditional on applying to the program, applicants are selected randomly.

Figure 4: Geographical Distribution of Applicants

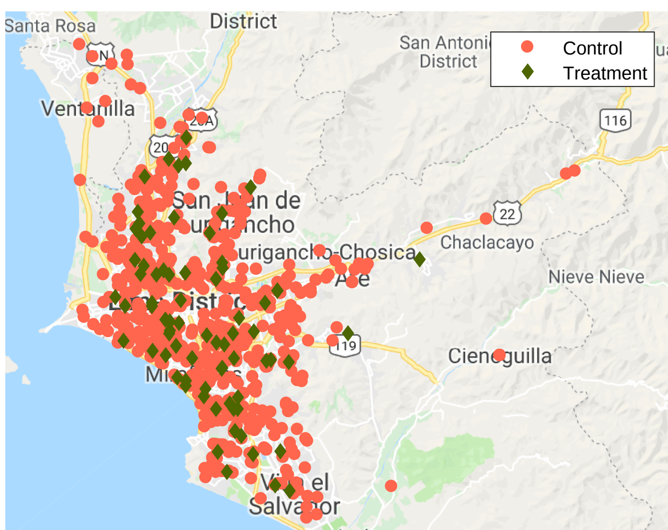
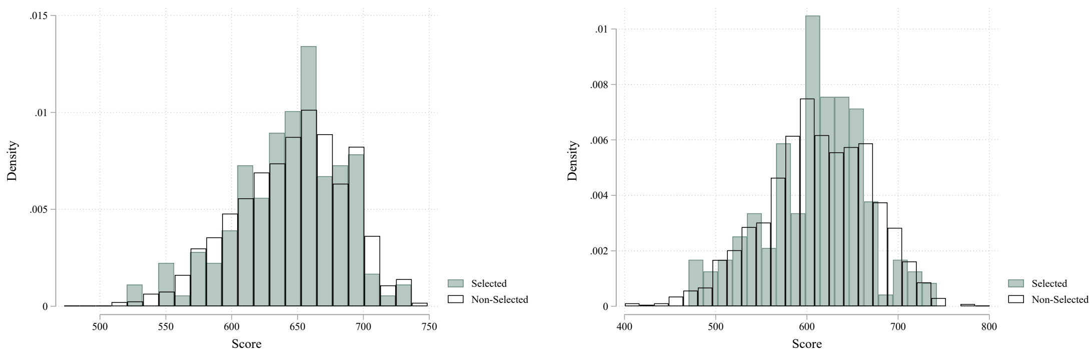


Figure 5: School Average on National Standardized Test for 2nd graders

(a) Spanish | (b) Mathematics



4.2 Empirical Strategy

Our empirical design relies on the lottery that the NGO runs every year. As showed before, conditional on applying, selection of the program participants is random. Therefore, this paper leverages on the random assignment to the scholarship and we use two main sources of data detailed in the previous section to study our outcomes of interest. We pool the data from every cohort since 2016 to 2019 and estimate the following equation:

$$y_{it} = \beta * Treat_{it} + \delta X_{it} + \phi_t + \epsilon_{it} \tag{1}$$

where y_{it} are the outcomes for each applicant i of a lottery cohort t, and t corresponds to years 2016 to 2019. $Treat_{it}$ is an indicator variable that equals to one if an applicant is randomly selected to participate in the program and β captures the treatment effect of the program. X_{it} are control variables (for precision) that include parent's education level (or school fee as a socioeconomic proxy when using the administrative data) and applicants' age, and ϕ_t are year fixed effects. Additionally, for the academic achievement results, we control for baseline grades. These estimations have robust standard errors using the Huber-White/sandwich estimator.

5 Results

5.1 Academic Achievement

In this section, we study the effects of the program on grades. We use administrative data from the Ministry of Education collected from every school at the end of the academic year.

We estimate Equation (1) including baseline controls for each subject performance from the previous academic year. As seen on 6, we find slightly negative effects on math, religion, Spanish and arts and near zero effects on science and social sciences. Figure 7 shows that after on 1 year of the program participation, the results look in opposite direction to the participation year, showing some evidence of a ”catching-up” effect that continues after 2 years of participating in the program as seen in Figure 8. Overall, given the lack of significance in our estimates, we interpret that the program had no effects in academic performance. We want to highlight that the program itself was not remedial school and in fact, it had no relationship with the school curricula. Thus the only possible channel where the program could have any effects on grades was through behavioral changes, which we consider as our first stage. We discuss these results in the next section.

Figure 6: Grades results during the treatment year

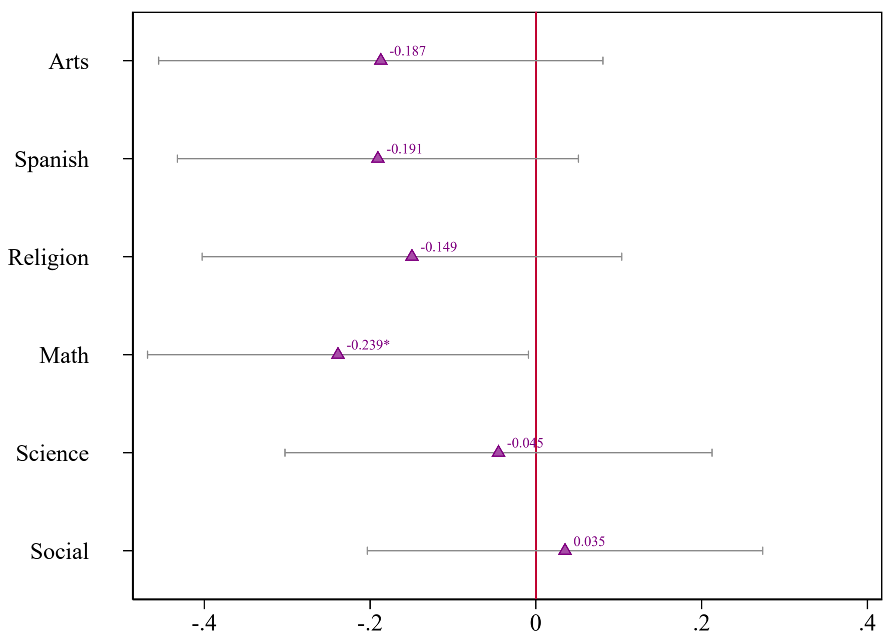


Figure 7: Grades results 1 year after treatment

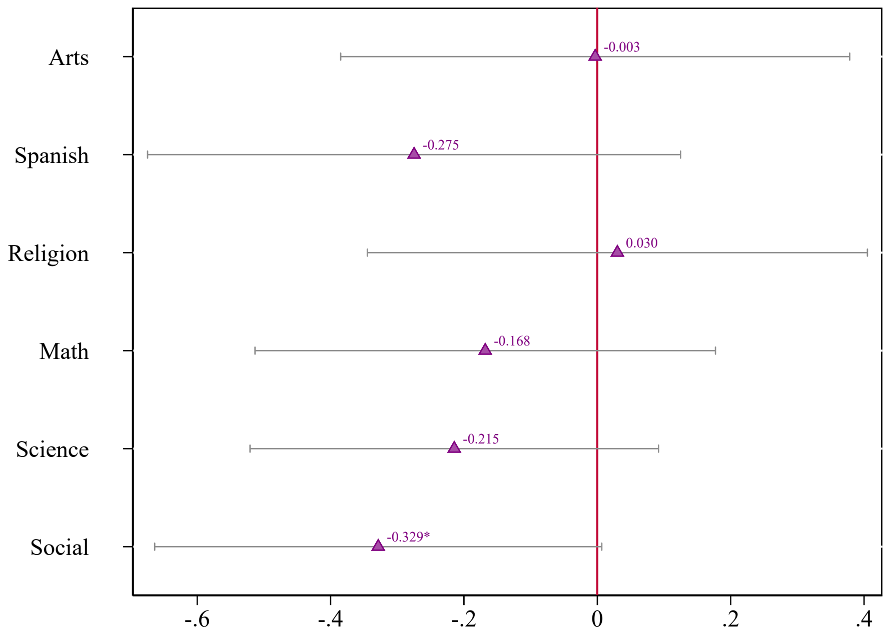
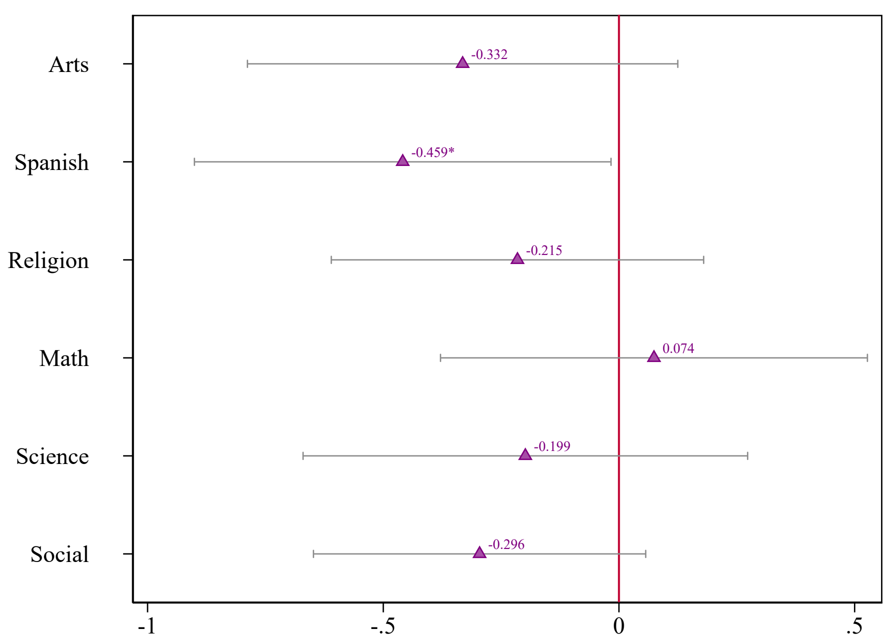


Figure 8: Grades results 2 years after treatment



5.2 Behavioral Responses

Perceptions on Ability and Grades: We asked parents and applicants to rate their ability and achievement (grades) in different subjects in a scale from 0 to 100. We find no significant effects on applicants' perceptions of ability, both on STEM and non-STEM subjects as seen on Figure 9 (a). However, when looking at perceptions of grades, we see that admitted girls are more confident about their grades in all subjects except Spanish. In particular, we find significant effects, a 5 percent increase relative to the control group, on Science as seen on Figure 9 (b), suggesting that treated girls are more like to be confident about their grades in this course. We do not find significant effects on parents' perceptions nor in differences between parents and applicants' responses. Overall, we see evidence suggesting that treated girls tend to be more confident about their grades relative to their parents' perceptions as seen in Appendix Figure A.28. We also asked both parents and applicants about their effort at school and we find no significant effects albeit negative as seen on Table 2.

Table 2: Effort at School

	Parent		Applicant		Difference	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-1.716	-1.875	-0.525	-0.866	-1.531	-1.311
	(1.833)	(1.908)	(2.114)	(2.191)	(1.439)	(1.480)
Controls	No	Yes	No	Yes	No	Yes
Mean	88.63	88.63	85.90	85.90	2.878	2.878
Obs.	350	349	338	337	338	337

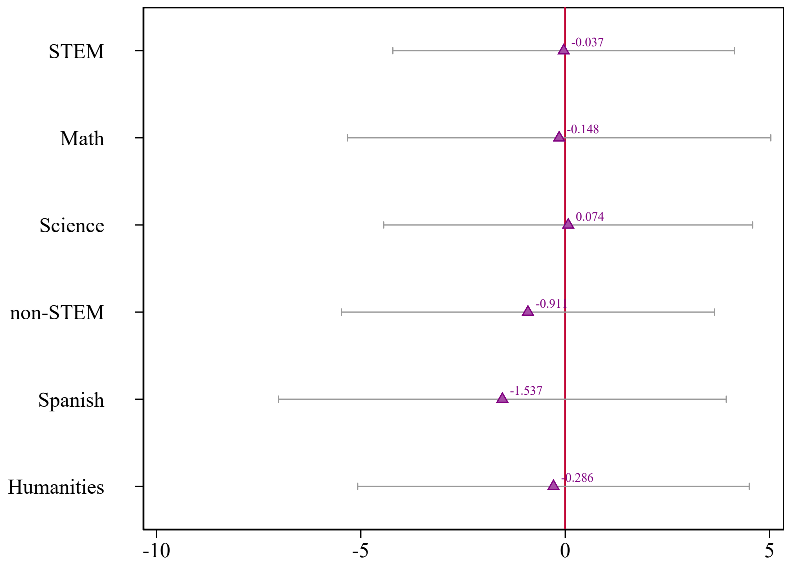
All models have year FE. Controls: parents; education , applicant's age, and a dummy that indicates whether the girl applied more than once. Significance: *** p<0.01 ** p<0.05 * p<0.1.

Overconfidence in Academic Performance: As described before, the pool of applicants had higher grades in school compared to their peers in the classroom. We use a gaussian density to plot the difference of real - perceptions of academic performance calculated using deciles of the school-cohort distribution. We find no statistical difference between treatment and control group. Nevertheless, we highlight that for these particular results we have limited data. Figure 10 show the distribution of both treatment and control in STEM subjects. Notably, we see that the program had a higher effect on those students with the highest level of belief's distortion . This is not the case when we look at non-STEM subjects as in Figure A.30.

Time Use Effects: Figure 11 shows the effects on time use reported from applicants when we ask about a typical day (24 hours). We find significant positive effects on time spent on Personal Projects, which is consistent with some qualitative interviews we had with

Figure 9: Perceptions of Ability and Grades by Subject

(a) Ability



(b) Grades

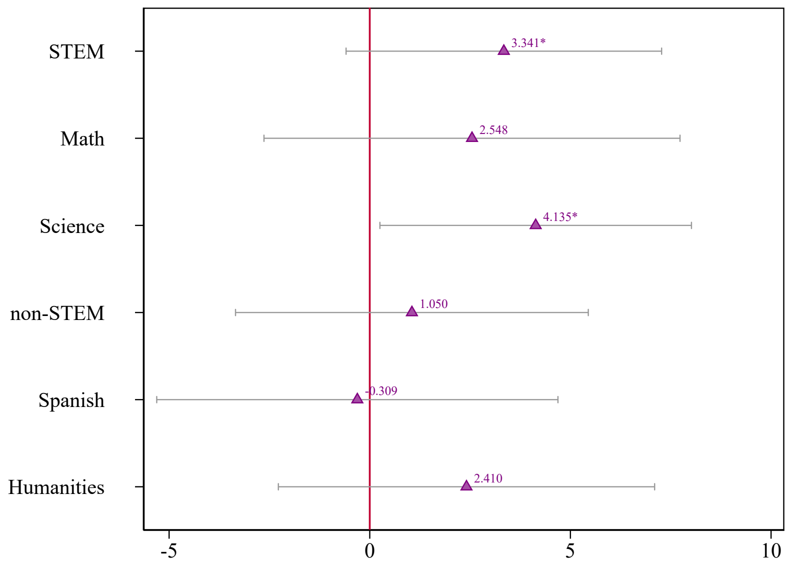
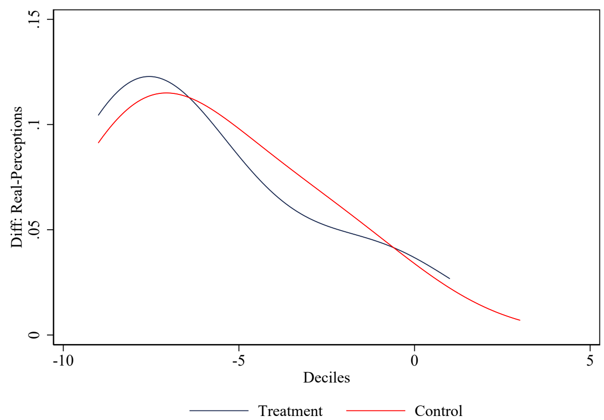
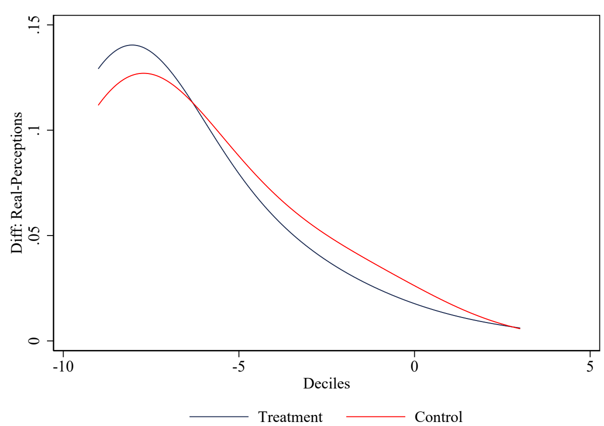


Figure 10: Overconfidence in STEM

(a) Math

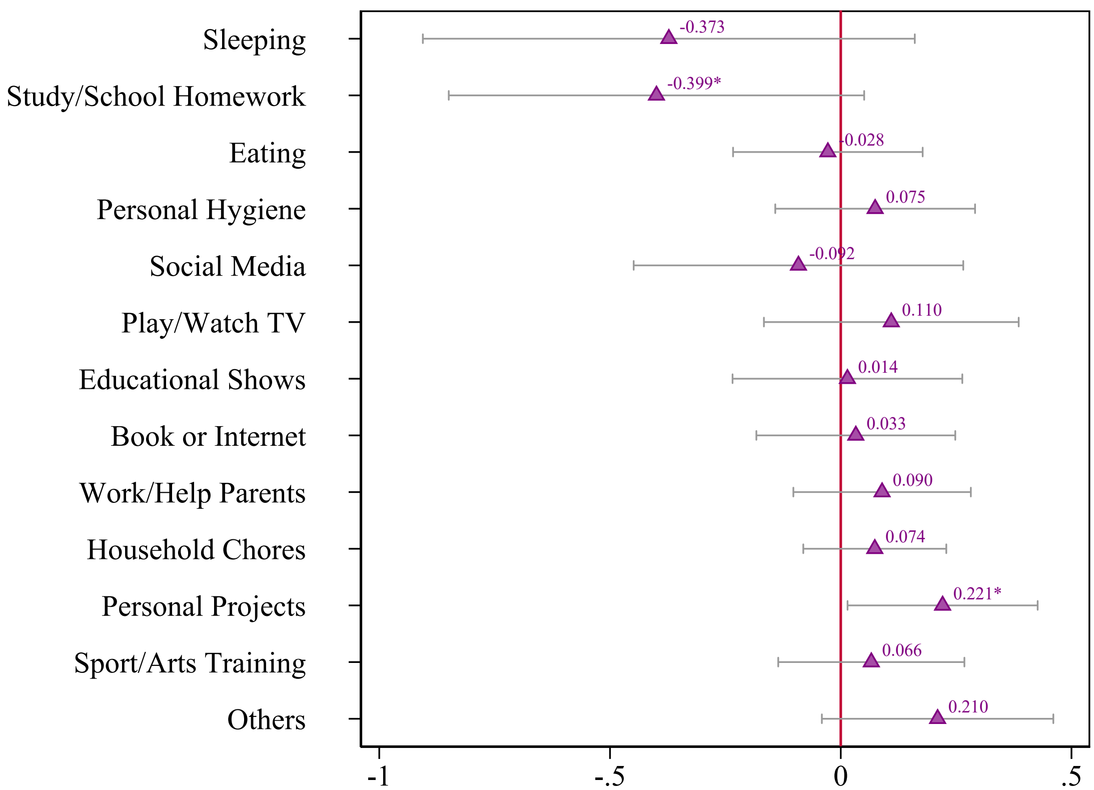


(b) Science



the NGO staff suggesting that participants reported starting their own science projects after concluding the program. The effect is 30 a percent increase that is equivalent to 10 more minutes on average. Also, we see significant negative effects on time spent in school homework. Girls spend on average 9 percent less time relative to the control group on homework and schooling, which is approximately 25 minutes. Additionally, we find negative effects on sleeping but these results are not significant. The findings so far suggest that girls might be more productive (as measured by their perceptions of their grades), use less time on school and trade it off with their own personal projects, which is consistent with the negative effects we see regarding their effort at school. Table 19 on Appendix shows the results with no controls, and the results are consistent as well.

Figure 11: Time Use Effects (Hours)



Perceptions about Majors in College: We ask how happy the applicant can be if they choose to follow a certain major (in a scale from 0-100). Figure 12 (b) shows a very clear path: there are negative significant effects on non-STEM careers (14 percent decrease relative to control group) mainly driven by majors like Law (24 percent decrease), Journalism (20 percent decrease) and Education (12 percent decrease) for treated girls. Surprisingly, in Figure 12 (b) we see small negative significant effects on Math and Architecture majors and no significant negative effects on Medicine and Engineering. One thing to highlight is that MaCTec's workshops were focused on topics related to biology and physics, and not mathematics. Given the selection into applying to the program that we documented before and that applicants have high interest in science to begin with, we deserve to take these results carefully.[9] On average, girls who applied to the program were already very enthusiastic about STEM careers. However, being exposed to this program and top scientists might have also made these girls more realistic about their chances of succeed at any career and decrease their overall confidence. In this sense, we do find that treated girls seem to be less pessimistic about Engineering and Medicine majors in comparison with other fields.[10]

The previous evidence is consistent with another measure: we asked applicants about their perceptions related to happiness for different major choices but for typical girls (same age and neighborhood). As seen in Figure 13 (b), there is a clear evidence of negative effects on STEM majors, following the same pattern as their own perceptions. Nevertheless, when looking at Non-STEM majors, treated girls are more pessimistic about their peers' likelihood to be happy on Education, Sociology or Arts. This finding might be explained by the fact that these majors are often low paid or considered less profitable in terms of labor markets outcomes. These graphs confirm our idea that overall, treated girls seems to be more pessimistic about the likelihood of being happy and succeed on any career, not only for themselves but also for girls like them.

Aspirations, Social Norms, Mental Health and Behavioral Outcomes: Inspired by Jayachandran (2015), we created an Aspiration Index, including 4 measures: probability of finishing high school with an outstanding grade, whether they talk with their parents about their future education, progressiveness of the occupation they will like to work on, and whether their major preference is STEM. We do not find significant effects on this index as seen on Table 3.

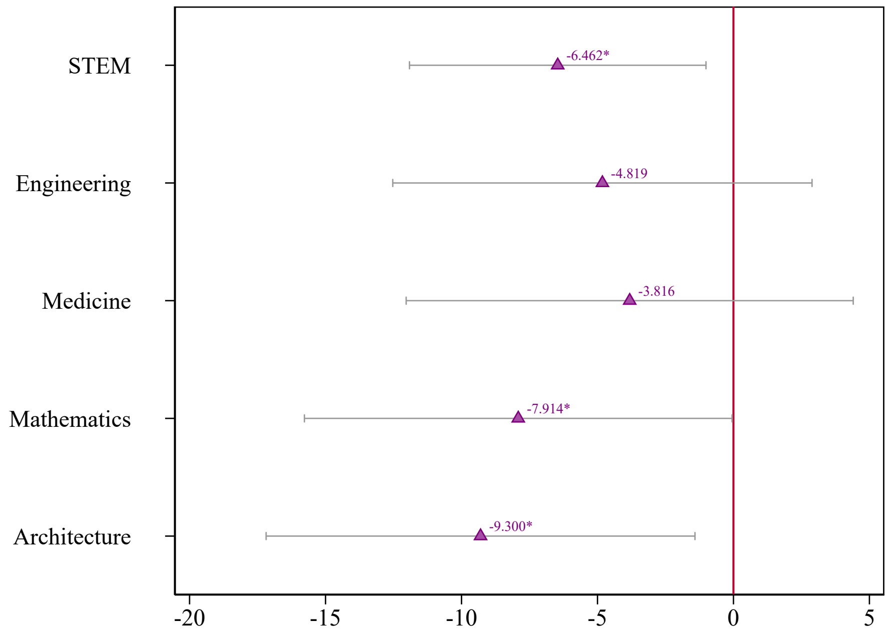
It is worth highlighting that there are significant negative effects on the likelihood of talking to their parents about their future. According to MacTec staff, most girls developed strength and independent as they were constantly challenged in weekly homework that

[9] For example, we do not find significant effects on their preferred major. Only a small positive but not significant effect on Health related majors. See Table 29 and 30.

[10] We also do not find effect when we asked the same question to parents, as seen on Appendix Tables 22 and Table 26.

Figure 12: Perceptions about Majors in College

(a) STEM



(b) Non-STEM

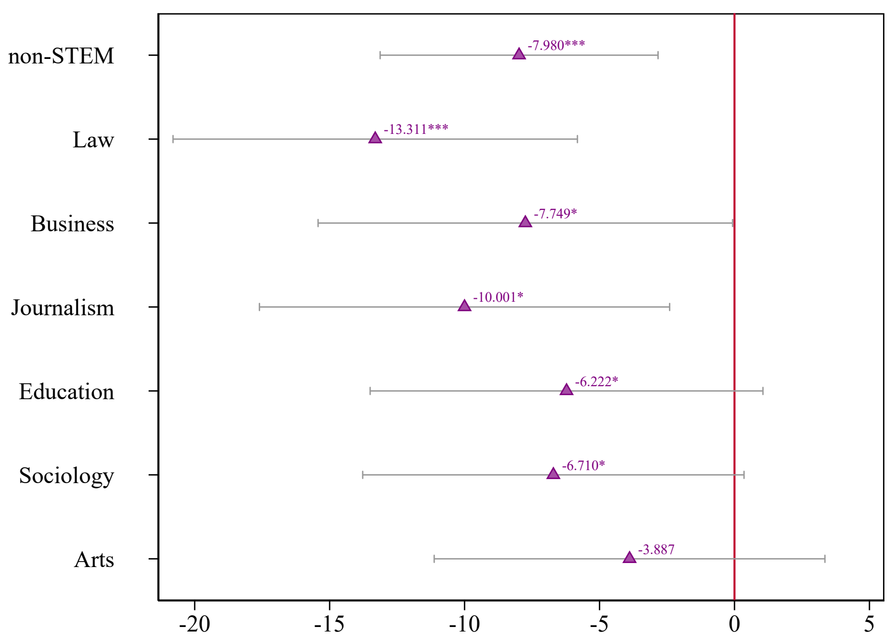


Table 3: Aspiration Index

	Finishing HS with 15+ GPA		Talked to parents about future		Progressiveness of occupation		Major preference is STEM		Aspiration Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	0.006	0.018	-0.352**	-0.334*	0.100	0.087	-0.005	-0.007	-0.033	-0.027
	(0.122)	(0.122)	(0.170)	(0.173)	(0.120)	(0.122)	(0.127)	(0.129)	(0.083)	(0.084)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	338	337	330	329	309	308	315	314	298	297

Progressiveness of occupation is the average of Male-dominated status that preference has, which is, in turn, measured as the difference between the percentage of males and females in an occupation.
All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 4: Social Norms Vignettes

	Follows family advice		Marriage and lady-like career	
	(1)	(2)	(3)	(4)
Treated	-5.831**	-6.068**	0.087	-0.385
	(2.425)	(2.439)	(2.398)	(2.474)
Controls	No	Yes	No	Yes
Mean	19.46	19.46	11.54	11.54
Obs.	330	329	327	326

All models have year FE. Controls include parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1.

demanded public presentations and intense debates with lecturers. In some anecdotal conversations, some staff member mentioned that girls were also more intense in their manners and untimely compared to girls of the same age. Non surprisingly, when looking at the results on social norms, we also see that they are less likely to take and follow family advice regarding their future as seen on Table 4.

We also do not find significant effects on social norms regarding marriage and choosing a lady-like career, which might be consistent with the fact that most girls who applied to the program were already into STEM in the first place. We also see that girls in the treatment group show less grittiness and this is consistent across all components of this index, as seen on Table 7. Notably, we think that the pandemic could have exacerbated some of these traits and girls might feel worse given their high expectations and the limitations imposed by the strict lockdown.

Because this survey was implemented during the COVID-19 pandemic, we also asked some questions about their emotional state and how they were facing those stressful times. Table 5 shows a mental health index, that sheds a light on how girls see themselves. Girls in treated group reported feeling like they do not have many qualities, feeling less calm, feeling less likely to do things well and more stressed, but they do feel happy with themselves and full of energy. Their parents also reported that during the pandemic (and remote schooling) they were able to keep with the school homework, but social distance was affecting them. Even when these results are not significant, we take them as a sign that girls on the treatment group were negatively affected by the pandemic in terms of their mental health and emotions.

Table 5: Mental Health Index

	Happy with myself (1)	I have many qualitites (2)	I do things well (3)	I feel calm (4)	Not stressed (5)	I feel full of energy (6)	Mental Index (7)
Treated	0.119	-0.087	-0.140	-0.017	-0.011	0.021	-0.019
	(0.124)	(0.142)	(0.142)	(0.133)	(0.122)	(0.123)	(0.095)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	326	326	326	326	326	326	326

A higher score in mental index's individual components means better mental health.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
All models have year FE.
Significance: *** p<0.01 ** p<0.05 * p<0.1

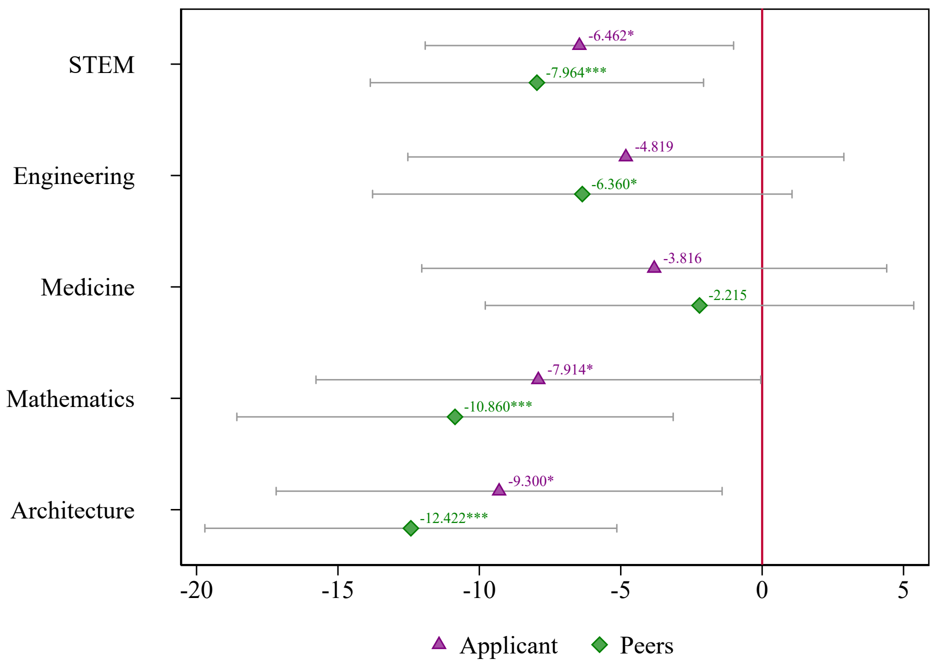
Table 6: COVID-19 Emotional State

	Discipline in school		Social distancing		Covid Coping Index	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.039	0.043	-0.052	-0.053	-0.007	-0.005
	(0.121)	(0.121)	(0.119)	(0.119)	(0.111)	(0.111)
Controls	No	Yes	No	Yes	No	Yes
Obs.	346	345	346	345	346	345

All models have year FE. Controls include parents' education , applicant's age, and a dummy that indicates whether the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1.

Figure 13: Perceptions about majors in college for applicants and their peers

(a) STEM



(b) Non-STEM

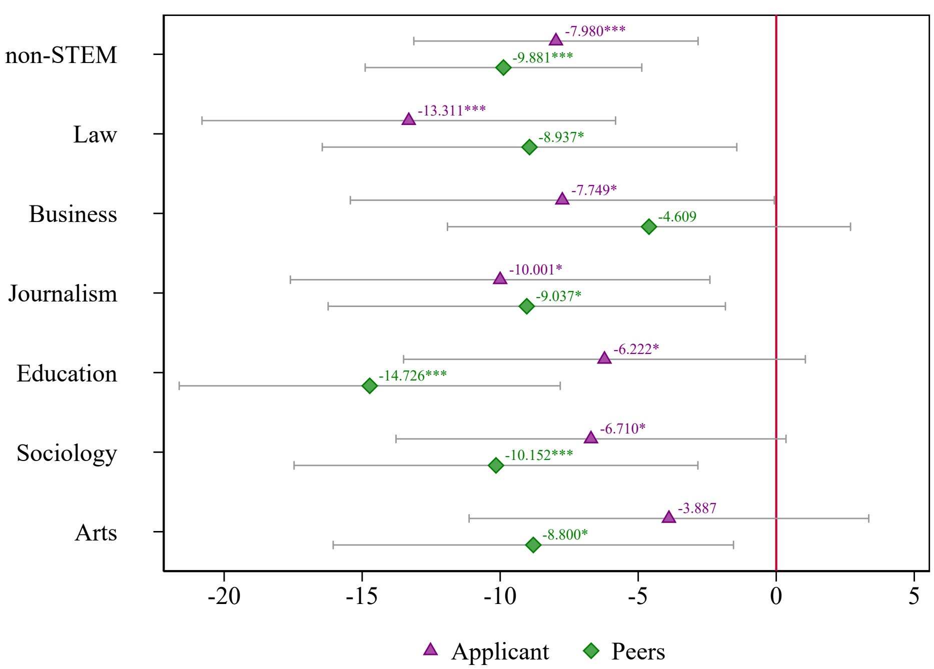


Table 7: Grit Index

	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Component 7	Component 8	Grit Index
Treated	-0.204	-0.323**	-0.204	-0.148	-0.157	-0.059	-0.314**	-0.350**	-0.220**
	(0.185)	(0.157)	(0.183)	(0.159)	(0.184)	(0.180)	(0.150)	(0.147)	(0.104)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	3.482	4.018	3.928	4.189	3.761	3.486	4.288	4.369	3.940
Obs.	326	326	326	326	326	326	326	326	326

Component 1: New ideas and projects do not distract me from previous ones. Component 2: Setbacks don't discourage me. Component 3: I have been obsessed with a certain idea or project without losing interest afterwards. Component 4: I am a hard worker. Component 5: I often set a goal and I do not stop until I complete it. Component 6: I do not have difficulty maintaining my focus on projects that take more than a few months to complete. Component 7: I finish whatever I begin. Component 8: I am diligent and I have initiative. A higher score in grit index's individual components means having more grit. All models have year FE. Significance: *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

6 Conclusions

According to Plan International (2018), Lima is one of the worst cities for women and girls in the world. Street harassment, domestic violence and sexual assaults are commonly heard on the news. Many of the gender issues occurring in Peru are due to social norms and stereotypes, which affect everyone in early stages of their lives. This paper studies a program that aims to empower young girls and boost their self-esteem and confidence in STEM, a highly man-dominated field, in a current context where gender violence is everyday news. What is more, the program we study has methodology of teaching that goes beyond increasing curiosity for STEM fields and works in a girls-only safe environment where girls are incentivized to work on abilities like speaking in public, debating and questioning, without shying away from boys.

This paper studies a novel private initiative that sheds a light on one of the most important topics related to gender inequality: low participation of female in STEM. These short-term results help understanding the mechanisms behind this program and its limitations as well. We leverage the lottery they used to select participants to provide strong evidence on both subjective (aspirations and beliefs) and objective outcomes (grades) to measure the effects of this program. We find no evidence of effects on academic performance measured by grades in school up to 2 years after the program participation. We find signs of overconfidence in science performance and no effects on effort or perceptions of ability. What is more, girls who participated in the program seem to be trading off school time to develop personal projects. Given that, on average, there was still room to improve grades, we believe that the program deviates girls' attention from school to other activates outside school, suggesting that they are not allocating their time optimally. This is consistent with signs of less grit and more mental stress. Nevertheless, further research on long-term outcomes should be considered.

This paper brings new and relevant contributions to the literature. To our knowledge, there are not many papers that study STEM aspirations at such a young age and most interventions that aim to incentivize women in STEM have worked with adolescents in secondary school or recent high school graduates. What is more, examining the impacts of this program and its limitations will also help designing future scale-ups and replications in other similar settings, given the extensive analysis we provide on selection. Targeting participants should be considered given that our results suggest that girls who applied to the program were already at the top of the distribution, leaving little margin to improve academically.

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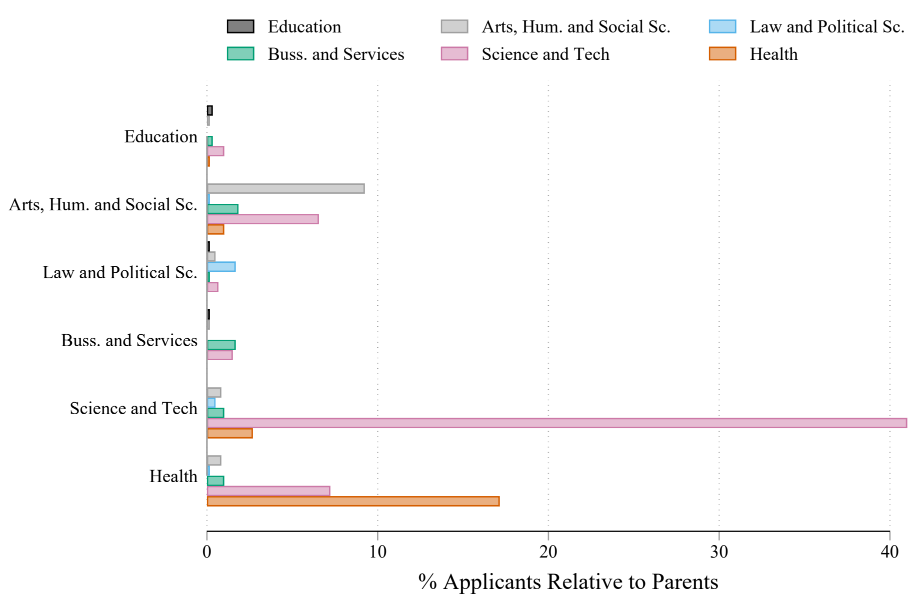
A Appendix

A.1 2019 Baseline Results

In this section, we analyze the results from the baseline taken in 2019, which provides a nice setting for a descriptive analysis of the program. Every year, MacTec organizes a round of applications for the program starting on January 1st. In 2019, the researchers participated on this process and they modified the application questionnaire, collecting data on 754 applicants. This baseline was mainly designed to capture basic information about families and some indicators of beliefs, stereotypes and aspirations.

We find that 78% of people filling out the survey are the applicant's mother and the average age of parent or tutor is 40 years old. Also, we find that parents are highly educated: 90% of them have done some higher education and what is more, 50% have completed a college degree, which is consistent with our analysis on selection. Only 1% of parents/tutors have a native language different than Spanish (i.e., Quechua or Aymara). Additionally, 30% of applicants live in 4 districts out the 44 in Metropolitan Lima. They come from households with an average size of 4.8 people, so 47% of applicants have one sibling and 25% are single children. Most applicants are in 3rd and 4th grade.

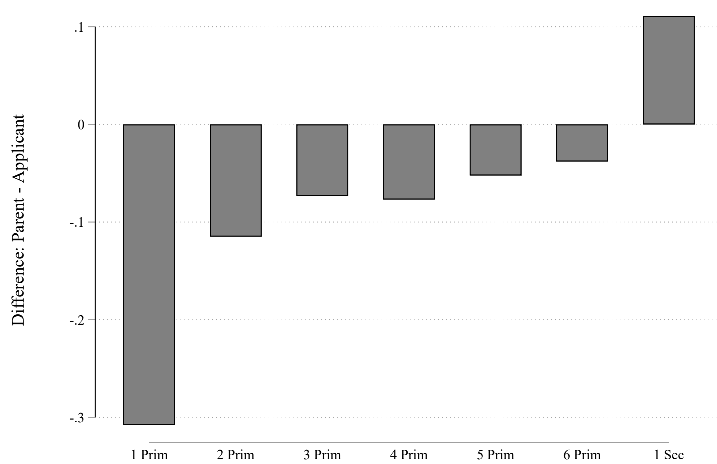
Figure A.14: Major Choice Expectations



Regarding aspirations and as expected, most parents say they expect their daughters to finish college and then work. We also ask, conditional on going to college, what major they wish their daughter follow and 58% expect their daughters to follow a STEM major. This is also highly correlated with their daughter's expectations, as seen in Figure A.14, where we plot the shares relative to their parents' preferences.

Regarding school, most parents agree their daughters are better at math and science, but 30% of them said that their daughter are good at *all* subjects. When we asked parents how much effort does the applicants put into school, 56% replied *what is needed* while 40% replied *a lot* and the rest, *little or almost none*. However, when comparing to the applicant's responses, (i.e, difference of tutor minus applicant's answers), we find that parents tend to underestimate their daughters' effort. We also find that it corrects overtime: parents underestimate their daughters when they are very young but overestimate when older as seen in Figure A.15. [11]

Figure A.15: Biases on Effort at School by Grade

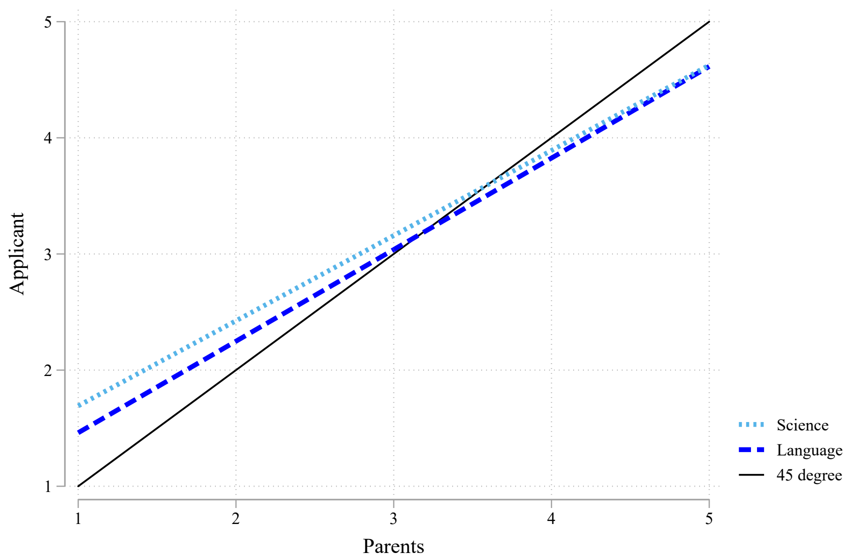


In terms of academic achievement, we find that most parents think their daughter gets better grades in STEM subjects and 30% said that the applicant is good in *all* subjects. This will suggest that parents tend to overestimate their daughters in both academic performance and ability. When comparing with the applicant's answers - where we ask the same questions regarding ability in some subjects (STEM vs non-STEM), we find some biases. As Figure A.16 shows, girls tend to be more optimistic relative to their parents for lower levels of ability while in higher levels, girls tend to be more pessimistic relative to their parents. And what is more, there is a small sign of overestimating abilities in non-STEM and un-

[11]Read Figure A.15 carefully, both 1st graders of primary and secondary school have very little observations so we cannot extract meaningful conclusions from both extremes.

derestimating on STEM (parents relative to applicants). Both measures are significant and positively correlated, meaning that parents over/under estimate their daughters ability both in STEM/non-STEM together.

Figure A.16: Biases on Ability - Applicants relative to Parents



We also ask about stereotypes, mainly if there are biases for against women in STEM and non-STEM subjects, and we do not find significant differences. This might be because the questions were too straight forward, and the "right" answer is quite obvious. We ask the same question both applicants and their parents/tutors, so we compared their answers relative to each other. In both questions, most of parents and applicants said that both women and man are equally good, but this was more intense among parents. There was 20% of applicants said girls were better suggesting they might be more positively biased than their parents. Finally, we asked applicants questions about their preferences and aspirations. As expected, most girls reveled that their favorite subject at school were STEM and 30% said *all subjects* were their favorite.

Figure A.17: Major Choice Preference

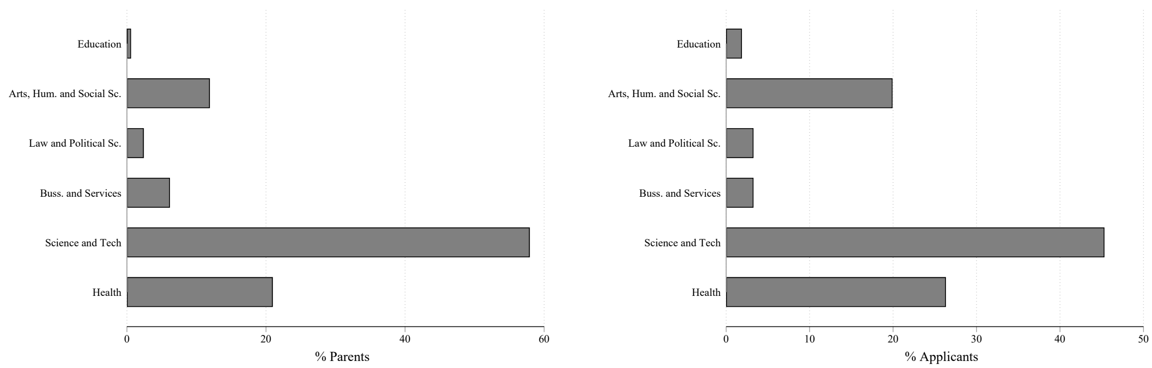


Table 8: Applicants' Favorite Subject

Subject	Count	Percent
Math	248	33
Science	222	29
Language	61	8
Social Sciences	66	9
All	104	14
None	8	1
Other	45	6
Total	754	100

Figure A.18: Biases on Effort at School

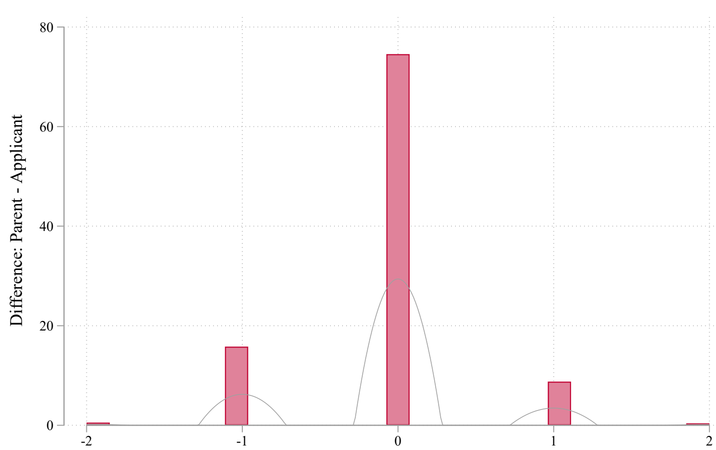


Figure A.19: Beliefs on Ability - Applicants

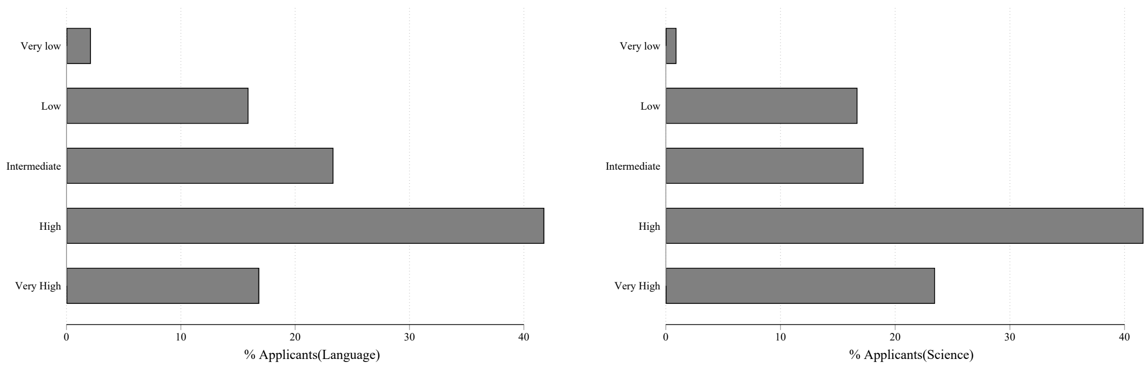


Figure A.20: Beliefs on Ability - Tutors

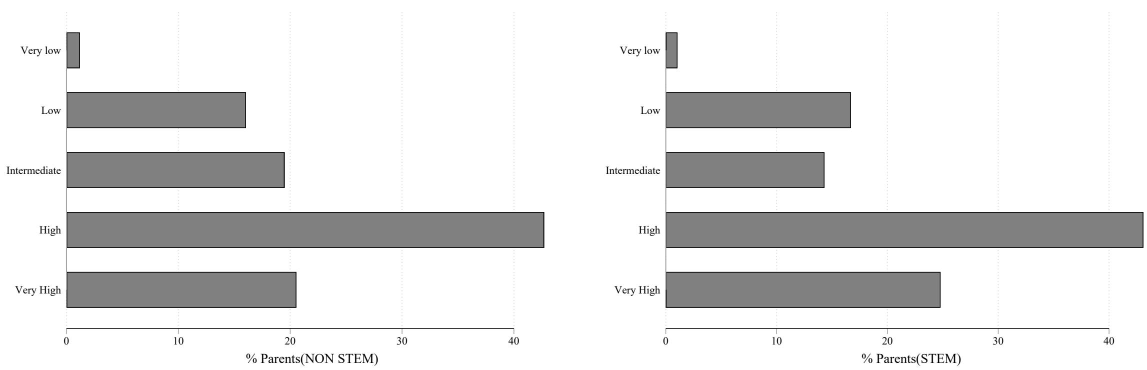


Table 9: For which subject does your daughter have better academic achievement?

Subject	Number	Percent
Math	246	33
Science	181	24
Language	62	8
Social Sciences	32	4
All	224	30
None	2	0
Other	7	1
Total	754	100

Table 10: Who does it better?- Applicant

Statement	No STEM Count	Percent	STEM Count	Percent
Girls are better	211	28	216	29
Boys are better	34	5	29	4
All are good	475	63	487	65
Dont know	34	5	22	3
Total	754	100	754	100

Table 11: Who does it better?- Parents/Tutor

Statement	No STEM Count	Percent	STEM Count	Percent
Women are better	69	9	50	7
Men are better	6	1r	20	3
All are good	674	89	675	90
Dont know	5	1	9	1
Total	754	100	754	100

A.2 Additional Results

A.2.1 Selection

Figure A.21: Selection on School Characteristics as a Socio-Economical Measure

(a) Extreme Poverty Share

(b) Private School Fees

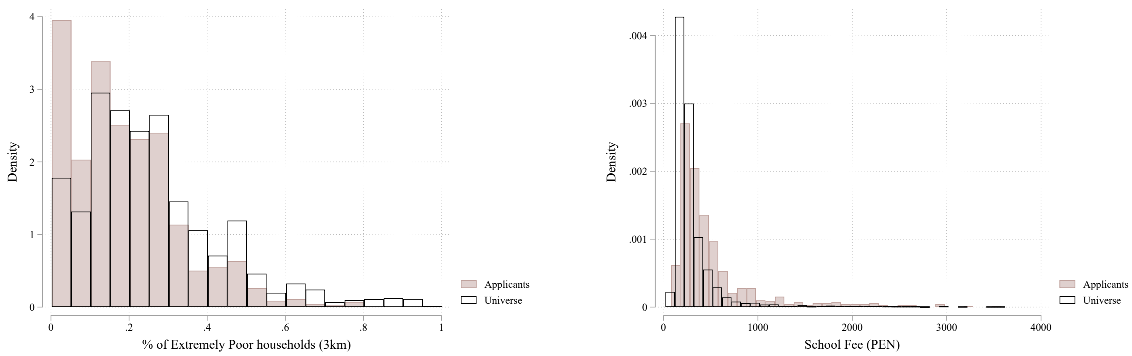


Figure A.22: Where do the applicants come from?

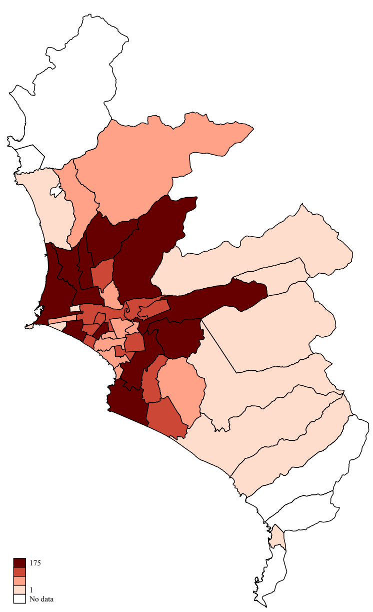
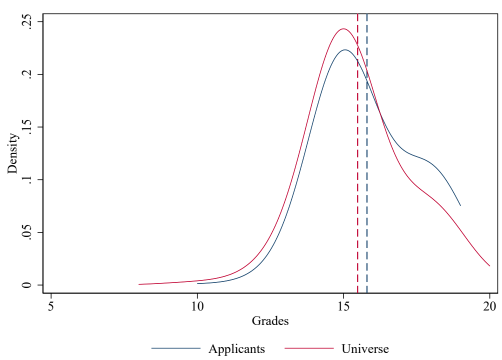
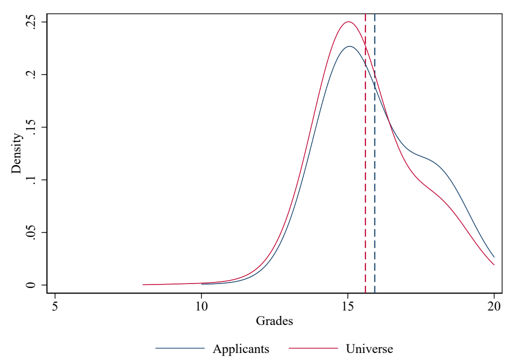


Figure A.23: School Grades Selection in Non-STEM Subjects

(a) Spanish



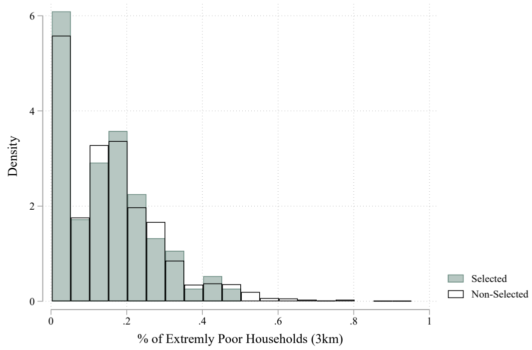
(b) Social Sciences



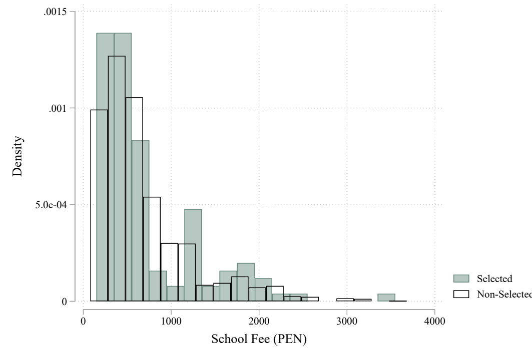
A.2.2 Randomization

Figure A.24: School as a Socio-Economical Measure

(a) Extreme Poverty Around School



(b) Private School Fees



A.2.3 Endline Implmentation

Table 12: Balance Control and Treatment on Endline Survey

Variable	(1) Control	(2) Treatment	(3) Difference
Applicant's age	9.612	9.464	-0.092
	(1.187)	(1.039)	(0.137)
Applicant's grade	4.547	4.414	-0.135
	(1.354)	(1.247)	(0.160)
Parent/tutor completed college or more	0.618	0.598	-0.023
	(0.487)	(0.492)	(0.059)
School is public	0.161	0.211	0.060
	(0.368)	(0.410)	(0.047)
Poverty Around School	0.158	0.143	-0.010
	(0.129)	(0.116)	(0.016)
School fee (PEN)	606.467	625.476	1.390
	(479.223)	(467.449)	(67.118)
ECE Spanish	645.864	645.854	-0.262
	(43.195)	(39.782)	(5.314)
ECE Math	609.963	610.308	1.491
	(57.029)	(52.754)	(7.026)
No. Teachers	23.902	23.899	-1.077
	(16.694)	(17.385)	(2.054)
No. Students	424.647	421.165	-14.333
	(295.140)	(335.342)	(37.668)
Observations	238	112	350

A.2.4 Academic Achievement Results

Figure A.25: Relative Grades Results: During the treatment year

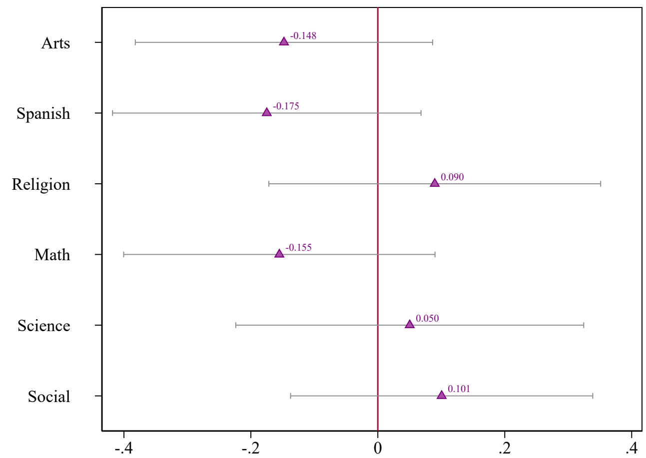


Figure A.26: Relative Grades Results: Including 1 year after treatment

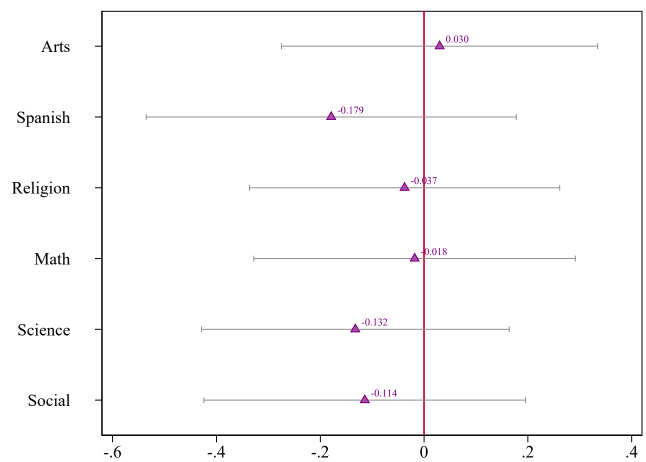
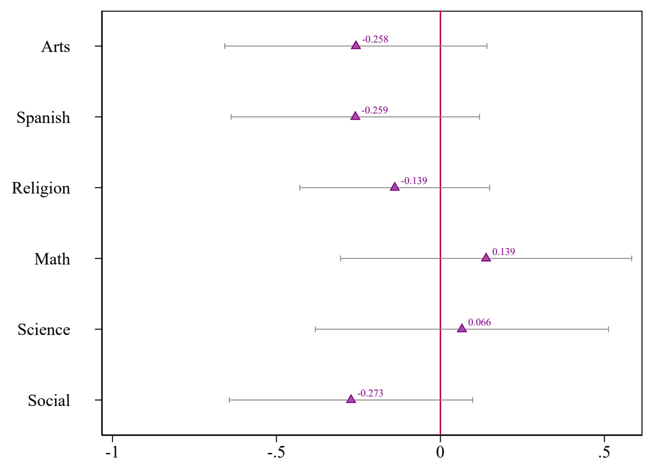


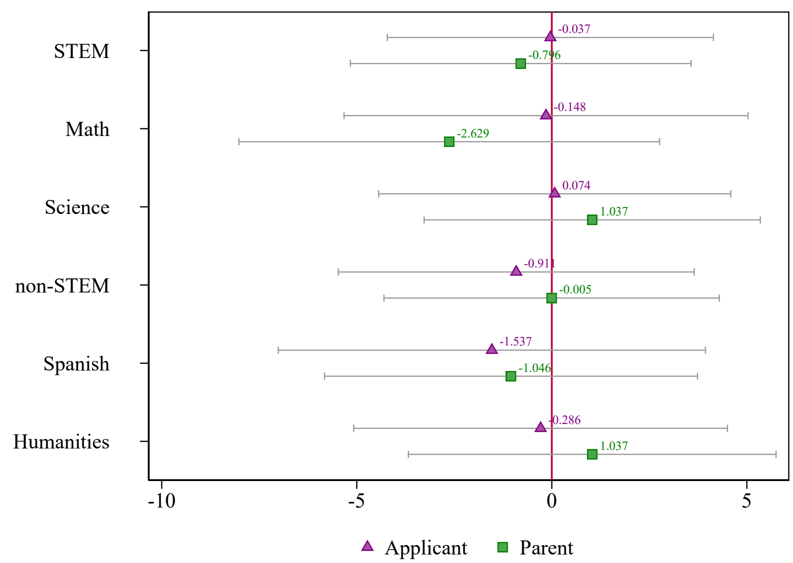
Figure A.27: Relative Grades Results: Including 2 years after treatment



A.2.5 Beliefs about ability, grades and effort at School

Figure A.28: Perceptions on Ability and Grades by Subject

(a) Ability



(b) Grades

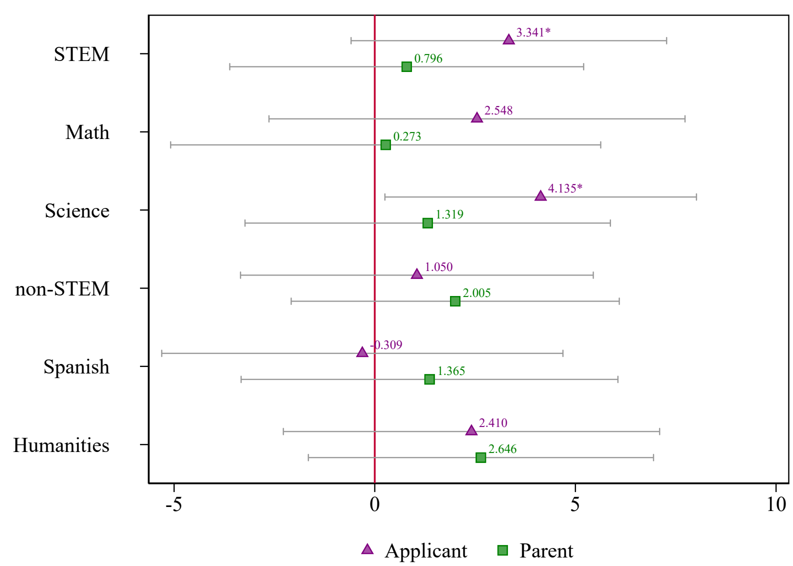


Table 13: Applicant's self-perception on ability

	STEM						Non-STEM					
	Avg.		Math		Science		Avg.		Spanish		Humanities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	0.204	-0.037	0.151	-0.148	0.257	0.074	-0.735	-0.911	-1.327	-1.537	-0.143	-0.286
	(2.076)	(2.125)	(2.605)	(2.633)	(2.217)	(2.294)	(2.243)	(2.319)	(2.696)	(2.784)	(2.371)	(2.435)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	82.35	82.35	80.14	80.14	84.55	84.55	81.27	81.27	81.57	81.57	80.97	80.97
Obs.	338	337	338	337	338	337	338	337	338	337	338	337

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 14: Parent's perception on daughter's ability

	STEM						Non-STEM					
	Avg.		Math		Science		Avg.		Spanish		Humanities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	-0.515	-0.796	-2.076	-2.629	1.047	1.037	-0.035	-0.005	-0.868	-1.046	0.798	1.037
	(2.197)	(2.220)	(2.711)	(2.741)	(2.138)	(2.191)	(2.139)	(2.185)	(2.403)	(2.431)	(2.331)	(2.396)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	84.65	84.65	82.73	82.73	86.58	86.58	80.69	80.69	81.42	81.42	79.97	79.97
Obs.	350	349	350	349	350	349	350	349	350	349	350	349

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 15: Parent-applicant difference on ability perception

	STEM						Non-STEM					
	Avg.		Math		Science		Avg.		Spanish		Humanities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	-0.937	-1.026	-2.248	-2.559	0.374	0.508	0.588	0.709	0.546	0.450	0.631	0.967
	(1.974)	(1.916)	(2.317)	(2.250)	(2.281)	(2.267)	(2.038)	(2.027)	(2.641)	(2.696)	(2.282)	(2.253)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	2.421	2.421	2.655	2.655	2.188	2.188	-0.419	-0.419	0.0218	0.0218	-0.860	-0.860
Obs.	338	337	338	337	338	337	338	337	338	337	338	337

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 16: Applicant's self-perception on grades

	STEM						Non-STEM					
	Avg.		Math		Science		Avg.		Spanish		Humanities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	3.509*	3.341*	2.924	2.548	4.094**	4.135**	1.070	1.050	-0.144	-0.309	2.284	2.410
	(1.975)	(1.999)	(2.600)	(2.635)	(1.923)	(1.973)	(2.196)	(2.234)	(2.499)	(2.541)	(2.319)	(2.383)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	81.19	81.19	79.44	79.44	82.94	82.94	80.28	80.28	81.21	81.21	79.35	79.35
Obs.	338	337	338	337	338	337	338	337	338	337	338	337

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 17: Parent's perception on daughter's grades

	STEM						Non-STEM					
	Avg.		Math		Science		Avg.		Spanish		Humanities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	1.112	0.796	0.672	0.273	1.551	1.319	2.003	2.005	1.598	1.365	2.408	2.646
	(2.178)	(2.242)	(2.653)	(2.724)	(2.245)	(2.314)	(2.001)	(2.078)	(2.308)	(2.387)	(2.100)	(2.186)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	83.62	83.62	81.88	81.88	85.36	85.36	80.33	80.33	81.25	81.25	79.42	79.42
Obs.	350	349	350	349	350	349	350	349	350	349	350	349

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 18: Parent - applicant difference on grades perception

	STEM						Non-STEM					
	Avg.		Math		Science		Avg.		Spanish		Humanities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	-2.443	-2.655*	-1.942	-2.062	-2.944	-3.248*	0.808	0.787	1.658	1.532	-0.041	0.042
	(1.507)	(1.514)	(1.703)	(1.675)	(1.917)	(1.952)	(1.757)	(1.788)	(2.242)	(2.284)	(1.855)	(1.886)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	2.493	2.493	2.389	2.389	2.598	2.598	0.0808	0.0808	0.0873	0.0873	0.0742	0.0742
Obs.	338	337	338	337	338	337	338	337	338	337	338	337

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Figure A.29: Overconfidence in Spanish

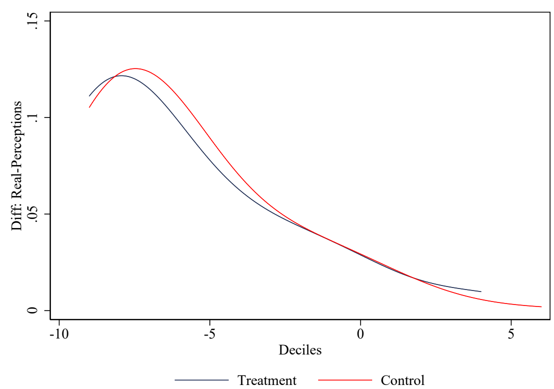


Figure A.30: Overconfidence Humanities and Social Sciences

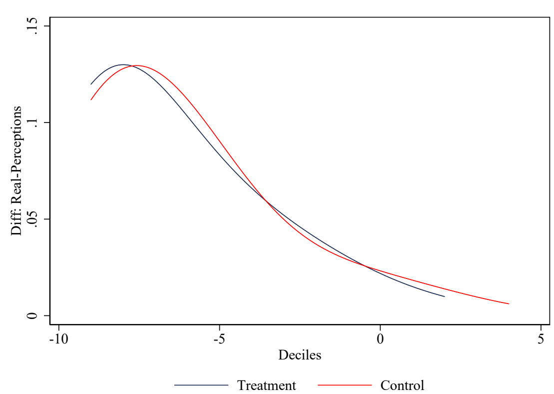
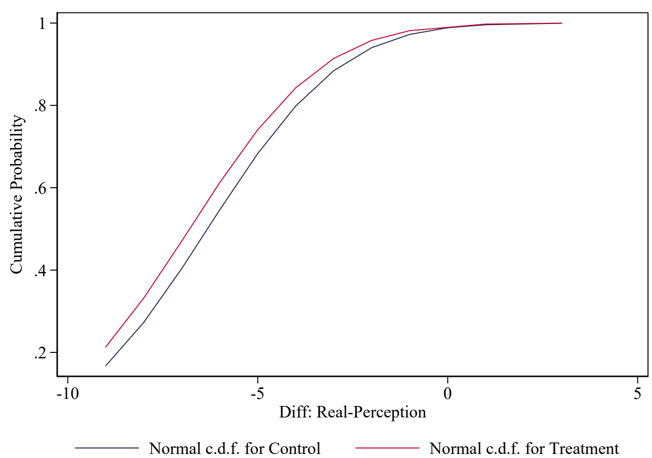


Figure A.31: Overconfidence in Science and CDF by Treatment Status



A.2.6 Time Use

Table 19: Time Use Effects, no controls

	Sleeping	Study and School Homework	Eating	Personal Hygiene	Social Media	Play or Watch TV	Educational Shows	Books or Internet	Work/Help Parents	Household Chores	Personal Projects	Sport/Arts Training	Others
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Treated	-0.329	-0.401*	-0.038	0.058	-0.127	0.126	0.023	0.014	0.071	0.081	0.227**	0.070	0.225*
	(0.273)	(0.229)	(0.104)	(0.107)	(0.185)	(0.137)	(0.129)	(0.111)	(0.097)	(0.080)	(0.103)	(0.101)	(0.127)
Controls	No	No	No	No	No	No	No	No	No	No	No	No	No
Mean	7.748	5.351	1.761	1.203	1.180	1.212	1.077	1.113	0.595	0.869	0.698	0.910	0.284
Obs.	327	327	327	327	327	327	327	327	327	327	327	327	327

All models have year FE.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 20: Time Use Effects, with controls

	Sleeping	Study and School Homework	Eating	Personal Hygiene	Social Media	Play or Watch TV	Educational Shows	Books or Internet	Work/Help Parents	Household Chores	Personal Projects	Sport/Arts Training	Others
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Treated	-0.373	-0.399*	-0.028	0.075	-0.092	0.110	0.014	0.033	0.090	0.074	0.221**	0.066	0.210
	(0.271)	(0.229)	(0.104)	(0.110)	(0.181)	(0.140)	(0.127)	(0.110)	(0.098)	(0.079)	(0.105)	(0.103)	(0.127)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	7.748	5.351	1.761	1.203	1.180	1.212	1.077	1.113	0.595	0.869	0.698	0.910	0.284
Obs.	326	326	326	326	326	326	326	326	326	326	326	326	326

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

B Perceptions and Major Choice

B.1 Perceptions in STEM Majors

Table 21: Applicant's perception of STEM major

	STEM avg.		Eng.		Medicine		Maths		Architecture	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	-6.592**	-6.462**	-5.297	-4.819	-4.000	-3.816	-8.075**	-7.914**	-8.996**	-9.300**
	(2.710)	(2.771)	(3.846)	(3.919)	(4.122)	(4.178)	(3.927)	(3.997)	(3.929)	(4.008)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	65.50	65.50	67.67	67.67	65.78	65.78	61.61	61.61	66.91	66.91
Obs.	330	329	330	329	330	329	330	329	330	329

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 22: Parent's perception of STEM major

	STEM avg.		Eng.		Medicine		Math		Architecture			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)		
Treated	0.001	0.015	-0.353	-0.622	0.607	0.753	-0.970	-0.830	-2.334	-3.103	1.285	0.690
	(0.060)	(0.061)	(2.449)	(2.485)	(2.819)	(2.894)	(3.286)	(3.313)	(3.545)	(3.607)	(3.355)	(3.397)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	0.513	0.513	78.82	78.82	85.80	85.80	81.95	81.95	71.11	71.11	76.42	76.42
Obs.	350	349	350	349	350	349	350	349	350	349	350	349

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 23: Parent-applicant difference perception of STEM major

	STEM avg.		Eng.		Medicine		Math		Architecture	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	6.035**	5.688**	5.697	5.379	3.400	3.393	5.498	4.698	9.546**	9.281**
	(2.726)	(2.750)	(3.698)	(3.796)	(3.756)	(3.774)	(4.410)	(4.429)	(3.798)	(3.874)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	13.10	13.10	18.08	18.08	15.58	15.58	9.202	9.202	9.534	9.534
Obs.	330	329	330	329	330	329	330	329	330	329

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 24: Applicant's perception about peers in STEM major

	STEM avg.		Eng.		Medicine		Math		Architecture	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treated	-8.092***	-7.964***	-7.008*	-6.360*	-2.178	-2.215	-10.810***	-10.860***	-12.373***	-12.422***
	(2.928)	(2.995)	(3.710)	(3.770)	(3.805)	(3.851)	(3.913)	(3.921)	(3.628)	(3.702)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	64.08	64.08	64.65	64.65	67.34	67.34	58.07	58.07	66.26	66.26
Obs.	330	329	330	329	330	329	330	329	330	329

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

B.2 Perception in Non-STEM Majors

Table 25: Applicant's perception of non-STEM major

	Non-STEM avg.		Law		Business		Journalism		Education		Sociology		Arts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treated	-7.938***	-7.980***	-13.069***	-13.311***	-7.890**	-7.749**	-10.006***	-10.001**	-5.972*	-6.222*	-7.330**	-6.710*	-3.359	-3.887
	(2.580)	(2.617)	(3.823)	(3.808)	(3.874)	(3.903)	(3.803)	(3.863)	(3.605)	(3.699)	(3.532)	(3.591)	(3.631)	(3.679)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	57.39	57.39	55.35	55.35	60.69	60.69	50.86	50.86	49.35	49.35	48.97	48.97	79.14	79.14
Obs.	330	329	330	329	330	329	330	329	330	329	330	329	330	329

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 26: Parent's perception of non-STEM major

	Non-STEM avg.		Law		Business		Journalism		Education		Sociology		Arts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treated	0.977	0.909	-0.007	0.353	-2.924	-3.022	-0.243	0.096	1.747	1.492	2.795	2.317	4.491	4.219
	(2.828)	(2.866)	(3.784)	(3.806)	(3.430)	(3.463)	(3.874)	(3.894)	(3.725)	(3.756)	(3.702)	(3.730)	(3.370)	(3.438)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	63.68	63.68	64.05	64.05	74.68	74.68	54.83	54.83	58.93	58.93	56.92	56.92	72.63	72.63
Obs.	350	349	350	349	350	349	350	349	350	349	350	349	350	349

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 27: Parent-applicant difference in perception of non-STEM majors

	Non-STEM avg.		Law		Business		Journalism		Education		Sociology		Arts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treated	9.110***	9.148***	12.797***	13.430***	5.404	5.144	9.722**	10.022**	8.116*	8.269**	10.413***	9.486**	8.213**	8.540**
	(2.870)	(2.853)	(4.410)	(4.306)	(4.003)	(3.963)	(4.090)	(4.200)	(4.156)	(4.117)	(3.966)	(3.926)	(4.113)	(4.224)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	5.442	5.442	8.099	8.099	13.39	13.39	3.502	3.502	8.610	8.610	6.623	6.623	-7.578	-7.578
Obs.	330	329	330	329	330	329	330	329	330	329	330	329	330	329

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 28: Applicant's perception about peers in non-STEM careers

	Non-STEM avg.		Law		Business		Journalism		Education		Sociology		Arts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Treated	-9.469***	-9.881***	-8.738**	-8.937**	-4.624	-4.609	-7.965**	-9.037**	-13.591***	-14.726***	-10.352***	-10.152***	-8.702**	-8.800**
	(2.563)	(2.547)	(3.819)	(3.816)	(3.692)	(3.711)	(3.652)	(3.657)	(3.583)	(3.508)	(3.690)	(3.717)	(3.696)	(3.685)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	60.53	60.53	57.96	57.96	63.01	63.01	56.65	56.65	56.58	56.58	53.34	53.34	75.62	75.62
Obs.	330	329	330	329	330	329	330	329	330	329	311	310	311	310

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

B.3 Major Choice

Table 29: Applicant's major choice in STEM

	STEM avg.		Science		Health	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.002	-0.003	0.043	0.038	-0.062	-0.054
	(0.063)	(0.064)	(0.061)	(0.061)	(0.044)	(0.045)
Controls	No	Yes	No	Yes	No	Yes
Mean	0.574	0.574	0.354	0.354	0.202	0.202
Obs.	315	314	330	329	330	329

All models have year FE. Controls include parents' education, applicant's age, and a dummy that indicates whether the girl applied more than once. . Significance: *** p<0.01 ** p<0.05 * p<0.1.

Table 30: Applicant's major choice in non-STEM

	Non-STEM avg.		Humanities		Law		Education		Business		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	0.002	0.003	0.010	0.015	-0.037	-0.041*	0.001	-0.002	-0.012	-0.006	0.025	0.025
	(0.063)	(0.064)	(0.053)	(0.054)	(0.023)	(0.023)	(0.013)	(0.013)	(0.027)	(0.028)	(0.030)	(0.030)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	0.426	0.426	0.211	0.211	0.0628	0.0628	0.0135	0.0135	0.0717	0.0717	0.0538	0.0538
Obs.	315	314	330	329	330	329	330	329	330	329	330	329

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 31: Parent's preferred major choice in STEM

	STEM avg.		Science			Health
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.038	0.021	0.020	0.006	0.028	0.027
	(0.056)	(0.056)	(0.060)	(0.060)	(0.043)	(0.044)
Controls	No	Yes	No	Yes	No	Yes
Mean	0.717	0.717	0.513	0.513	0.168	0.168
Obs.	334	333	350	349	350	349

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

Table 32: Parent's preferred major choice in STEM

	Non-STEM avg.		Humanities		Law		Education		Business		Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	-0.038	-0.021	0.019	0.020	-0.005	-0.005	-0.014	-0.012	-0.037	-0.027	0.005	0.007
	(0.056)	(0.056)	(0.040)	(0.040)	(0.016)	(0.015)	(0.010)	(0.010)	(0.035)	(0.035)	(0.018)	(0.018)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean	0.283	0.283	0.0966	0.0966	0.0294	0.0294	0.00840	0.00840	0.113	0.113	0.0210	0.0210
Obs.	334	333	350	349	350	349	350	349	350	349	350	349

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1

B.4 Occupation Choice

Table 33: Preferred occupation, no controls

	Hard science (1)	Eng. (2)	Health (3)	Econ. (4)	Business Admin. (5)	Business Woman (6)	Law (7)	Humanities (8)	Teacher (9)	Languages (10)	Media (11)	Sports (12)	Military or Police (13)	Chef (14)	Arts (15)	Manual services (16)	Unsure (17)
Treatment	0.057	0.007	-0.056	-0.002	-0.020	0.012	-0.020	0.025	0.012	-0.014*	-0.011	-0.023**	0.008	-0.020	0.100*	0.026	0.038
	(0.049)	(0.056)	(0.056)	(0.011)	(0.022)	(0.022)	(0.026)	(0.022)	(0.019)	(0.008)	(0.026)	(0.009)	(0.012)	(0.027)	(0.054)	(0.018)	(0.025)
Controls	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Mean	0.186	0.245	0.327	0.0136	0.0409	0.0318	0.0682	0.0136	0.0227	0.0136	0.0409	0.0273	0.00455	0.0636	0.182	0.00455	0.0227
Obs.	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325	325

All models have year FE. Significance: *** p<0.01 ** p<0.05 * p<0.1.

Table 34: Preferred occupation, controls

	Hard science (1)	Eng. (2)	Health (3)	Econ. (4)	Business Admin. (5)	Business Woman (6)	Law (7)	Humanities (8)	Teacher (9)	Languages (10)	Media (11)	Sports (12)	Military or Police (13)	Chef (14)	Arts (15)	Manual services (16)	Unsure (17)
Treated	0.058	-0.000	-0.055	-0.001	-0.012	0.014	-0.020	0.029	0.010	-0.014*	-0.009	-0.021**	0.007	-0.027	0.100*	0.029	0.043*
	(0.048)	(0.056)	(0.058)	(0.012)	(0.021)	(0.024)	(0.027)	(0.023)	(0.019)	(0.009)	(0.026)	(0.009)	(0.011)	(0.028)	(0.054)	(0.019)	(0.025)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.186	0.245	0.327	0.0136	0.0409	0.0318	0.0682	0.0136	0.0227	0.0136	0.0409	0.0273	0.00455	0.0636	0.182	0.00455	0.0227
Obs.	324	324	324	324	324	324	324	324	324	324	324	324	324	324	324	324	324

All models have year FE.
Controls: parents' education, applicant's age, and a dummy if the girl applied more than once.
Significance: *** p<0.01 ** p<0.05 * p<0.1