Influencing Girls' Education Choices through Social Media Interventions: Evidence from Peru*

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Abstract

Although social media plays a central role in teenagers' lives, there is limited evidence on its potential to shape youths' preferences, aspirations and education choices. We conduct a randomized controlled trial in Peru to evaluate the impact of a role model intervention delivered via Instagram. Final-year high school girls were encouraged to engage with short Instagram video reels created by female engineering students depicting their academic and social experiences on campus. While the interventions initially reduced self-reported interest in engineering, particularly among girls who were least likely to go to college, it increased applications for an engineering scholarship among high-achieving girls in math. Most notably, the Instagram intervention led to a large increase in overall college enrollment, regardless of major. Although we find no increase in girls' engineering enrollment, the intervention increased enrollment in non-engineering STEM majors, particularly for top-performing girls. A complementary teacher information campaign delivered via WhatsApp reinforced the effects of the Instagram intervention for high-achieving girls while attenuating them for lower-performing students. Our study demonstrates the promise of leveraging widely-used social media platforms to engage young women and influence their higher education preferences and outcomes.

Keywords: Instagram, higher education, gender, Peru, experiment

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1 Introduction

Social media is a central part of teenage life across the globe. In the United States, teenagers spend over four hours a day on social media, with platforms like Instagram, Snapchat, and TikTok used daily by more than 70 percent of those aged 15 to 17 (Anderson et al., 2023). In Peru, the rapid expansion of broadband infrastructure over the last decade (More Sánchez and Argandoña Martinez, 2020) has similarly fueled widespread adoption of social media apps, including Instagram, especially among younger users.[1] While there is active public debate and a growing body of research on the possible effects of social media and smartphone use on teenagers' mental health and academic performance, with mixed findings (Beland and Murphy, 2016; Braghieri et al., 2022; Kessel et al., 2020; Kreski et al., 2021; Lichand et al., 2026), there is far less evidence on whether and how these platforms can influence adolescents' preferences, aspirations, and educational choices.

In this paper, we explore how social media can be leveraged to influence educational choice of teenage girls. We designed an Instagram intervention to increase interest in STEM post-secondary education among female high school students in Peru. Despite significant progress in women's access to higher education, female representation in STEM fields, particularly engineering, remains low in many countries. In Peru, only 30% of engineering applicants are women, and less than 10% of women in college major in engineering. While in-person exposure to female teachers and role models (Eble and Hu, 2018; Lim and Meer, 2020; Sevilla et al., 2023; Agurto et al., 2023; Breda et al., 2023; Porter and Serra, 2020) has shown promise, digital platforms, and especially social media, offer a compelling alternative for reaching adolescents at scale and at low cost.

We employ a randomized controlled trial to examine how "Instagram role models" targeting high school girls can impact post-secondary educational preferences and college enrollment choices. Specifically, we created an Instagram account called "My Days in University" (Mis Dias En La U) and invited final year female students in randomly selected high schools to follow the account (see Figure 1). These students were encouraged to engage with the content by liking a series of short videos posted on the account by female engineering college students over a total of 6 weeks. The short videos/reels documented the female students' experiences in college, while studying engineering, e.g., going to class, studying for homework, completing projects and interacting socially with other students.

[1] A recent survey suggests that two-thirds of adults in Peru use Instagram; however, accurate statistics for teenagers are not available. See https://www.statista.com/forecasts/1409959/social-network-usage-by-brand-in-peru.

Content consumed on Instagram differs from standard media content, e.g., television programming, in several important ways. First, content is posted more frequently and can appear in a user's feed multiple times within the same day or across multiple days. Second, the platform's recommendation algorithm personalizes content based on users' engagement, increasing exposure to similar content and creators when users like or spend time watching a reel (Narayanan, 2023; Metzler and Garcia, 2024). Third, engagement with reels and posts from one account may also influence the content recommended to users' friends, creating the potential for peer spillovers. Together, these features have the potential to reinforce exposure to relevant role models through repeated engagement with both the original account and similar accounts recommended by the algorithm.

The study involves 73 high schools in Peru, randomly divided into two treatment groups (48 schools combined) and one control group (25 schools). In the treatment schools, girls in the graduating class were encouraged to follow our Instagram account, which we set as "private", meaning that only approved users were granted access. Since previous studies (Carlana, 2019, e.g.,) have shown that teachers can play a crucial role in encouraging or discouraging girls to pursue study paths that challenge traditional gender roles, we complemented the Instagram intervention in about half of the treatment schools with a WhatsApp campaign targeting head teachers. Teachers received three short videos in which engineering professors discussed the gender imbalance in engineering and encouraged teachers to actively support female students interested in the engineering major.

We initially aimed to target all final-year female high school students in the sampled schools, in collaboration with school principals and head teachers. However, the requirement to obtain parental consent for social media content exposure and future tracking led to a final working sample of 547 girls, representing approximately 15 to 20 percent of the graduating class. Although the intervention and primary analysis focus on girls, we also surveyed a small sample of boys to enable gender gap comparisons in educational choices, bringing the total sample to 787 final-year students.

The Instagram intervention took place over 6 weeks in September and October 2023. We implemented a follow-up survey with the study participants immediately after the conclusion of the 6 weeks. We measured students' preferences regarding different educational and career paths, as well as their perceptions of their parents', teachers' and best friends' higher education preferences. About three months later, in December 2023, we offered all students the opportunity to apply for a small scholarship, which would be randomly awarded to one applicant, contingent on enrollment in an engineering major the following year. This scholarship application process served as a revealed preference measure for interest in engineering, as applying required filling out paperwork, making it

more likely that only students seriously considering an engineering major would apply.[2] Finally, in December 2024, we collected administrative data on the students' actual college enrollment, about one year after their high school graduation.[3]

Our findings indicate that the interventions had an immediate negative impact on girls' self-reported preferences for engineering, but no overall effect on scholarship applications. However, these aggregate findings mask important heterogeneity by math ability and baseline likelihood of college enrollment. Specifically, the decline in self-reported interest in engineering is driven by girls who are not top performers in math and by those who, based on their baseline characteristics, were unlikely to attend college. In contrast, the intervention had a large and statistically significant positive effect on scholarship applications among top-performing girls in math.

The administrative data on college enrollment show evidence of a large and positive impact of the interventions on college enrollment for *all* girls, regardless of major. Specifically, the Instagram intervention increases girls' likelihood of being enrolled in college one year after graduating from high school by 14.7 percentage points, i.e., a 55 percent increase from the 26.5 percent enrollment rate observed in the control group. While we do not find evidence of impacts on girls' enrollment in engineering, we see a significant increase in non-engineering STEM enrollment, particularly among top-performing girls. Further analysis indicates that the Instagram intervention increased girls' confidence in their ability to complete college (but not to pursue engineering studies), and shifted their beliefs about the likelihood that their best friends would attend college. Our data also provide suggestive evidence that the teacher information intervention reinforced the impact of the role model Instagram intervention for girls who were top performing in math, while reducing its effect for not-top-performing girls.

Our findings suggest that Instagram role model content may have reshaped girls' perceptions (or misperception) of university life and their potential for success in higher education, likely leading to the overall increase in college enrollment. These effects may have been further amplified by the Instagram algorithm itself, which could have exposed treated girls to similar content and accounts created by other college-going women, as well as through social influence within friendship networks if changes in treated girls' educational choices affected those of their peers.

[2]Given the small size of the scholarship, we do not expect it to have significantly shifted students' preferences. We anticipated the 2775 soles scholarship (about $750) to cover for about 4 months of room and board in a public university, or for enrollment fees and 1 month of tuition in a private elite university.

[3]College applications in Peru are typically submitted between October and December of the year preceding college enrollment. Universities have two terms, March to June, and August to November. Most enrollment by freshmen happens in the first term.

This study contributes to several bodies of work. First, we add to research on the factors that influence youths' educational preferences and choices, particularly the role of information, advising, and role models. Interventions that have proven successful have ranged from lifting financial and informational constraints (see, e.g., Dynarski et al., 2021), to tutoring and advising programs, implemented either in person, online or via text messages (see, e.g., Barr and Castleman, 2025; Bettinger et al., 2014; Carlana and La Ferrara, 2025; Castleman and Goodman, 2018; Cohodes et al., 2026).[4] An emerging literature examines whether less resource-intensive interventions based on exposure to relatable role models can also influence educational choices. Recent studies show that in-person exposure to role models can influence girls' aspirations, gender attitudes, self-confidence and perceptions of different fields of study and careers, often leading to changes in educational outcomes (Agurto et al., 2023; Breda et al., 2023; Kipchumba et al., 2024; Porter and Serra, 2020).[5] However, a large-scale study in Ecuador aimed at scaling up role model interventions through online, rather than in-person, exposure to multiple STEM role models found that the intervention reduced boys' and girls' interest in STEM fields and did not increase college enrollment (Asanov et al., 2026). We add to this work by showing that social media platforms heavily used by teenagers provide a promising channel for delivering scalable role-model interventions.

Our second contribution is to the literature on the economics of social media. Empirical studies in this space have primarily examined the impact of social media on political polarization, access to information, and misinformation (Aridor et al., 2024a,b). A smaller body of work has investigated the welfare effects of social media (Allcott et al., 2020; Bursztyn et al., 2023; Mosquera et al., 2020). These studies typically recruit participants through social media platforms, expose them to different content or incentives, and measure outcomes via follow-up surveys administered on the same platform or by tracking platform usage patterns. Our contribution to this literature is threefold. First, we recruit participants outside of the platform and measure real-life outcomes, moving beyond self-reported or platform-based metrics; in particular, we focus on impacts on post-secondary educational choices. Second, we specifically target teenagers and use Instagram, a platform widely used by younger generations but not targeted by previous social media interventions.[6] Third, we

[4]For a review of programs aimed at lifting non-financial barriers to student access to and success in college, see Dynarski et al. (2023).

[5]Related work shows that role models portrayed in movies and television programs can also influence educational outcomes (Riley, 2024), as well as women's fertility, empowerment and well-being (Jensen and Oster, 2009; La Ferrara et al., 2012; Kearney and Levine, 2015). Other studies have highlighted role model impacts on entrepreneurial aspirations (Batista and Seither, 2019; Bjorvatn et al., 2020). For a review of the impacts of exposure to traditional media on individual outcomes, see DellaVigna and La Ferrara (2015). For a review of role model interventions in low-income countries, see Serra (2025).

[6]Most social media experiments to date have been conducted on Facebook and Twitter, as documented in Aridor

introduce a novel approach to studying the effects of social media exposure on teenagers' preferences and behaviors: we created a dedicated Instagram account, invited participants to consume its content, and measured its effects on behaviors outside of the social media environment.

Finally, we provide suggestive evidence on the differential impacts that teachers could have on the post-secondary education outcomes of top- and lower-achieving girls. A growing literature shows that teachers' gender attitudes and stereotypes can influence girls' academic performance and their likelihood of pursuing male-dominated fields of study (Alan et al., 2018; Carlana, 2019; Lavy and Megalokonomou, 2024).[7] Our add-on teacher intervention suggest that initiatives explicitly targeting high-achieving girls, for instance to encourage their choice of a male-dominated field of study, may induce teachers to reallocate their time and attention toward these students.

While the Instagram intervention substantially increased overall college enrollment, changing girls' preferences for engineering proved more difficult, suggesting that encouraging entry into male-dominated fields may require more targeted and sustained interventions that also address the broader family and social constraints that shape study and career choices. More broadly, our study highlights the potential of leveraging social media platforms that are heavily used by teenagers to influence their educational choices. As internet access and smartphone use continue to expand in both high- and low-income settings, social media offers a low-cost and scalable channel to reach young people at a formative stage of their decision-making, potentially more directly, repeatedly, and personally than traditional school- or community-based outreach programs.

2 Context

The education system in Peru comprises six years of primary schooling followed by five years of secondary schooling, totaling 11 years. Attendance is compulsory from ages 5 to 16. At the secondary level, nearly 2.5 million students are enrolled in approximately 15,000 high schools across the country's 25 administrative regions. Secondary education is subject-based, with different teachers assigned to each subject, and the academic year runs from March to December.[8] All schools follow the national curriculum established by the Ministry of Education, which makes no distinction

et al. (2024a), but these platforms are far less popular among teenagers, who predominantly use Instagram, TikTok, and YouTube.

[7] Related studies have examined the impact of female teachers on girls' choice of male-dominated fields of study; see, for instance, Bettinger and Long (2005); Eble and Hu (2018); Lim and Meer (2020); Carrell et al. (2010).

[8] The national curriculum includes Mathematics, Communication, Foreign Language, Art, History, Geography, Economics, Civics, Social Skills, Physical Education, Religious Education, Science, Technology, and Environmental Studies.

between students intending to pursue STEM or non-STEM careers at any stage of primary and secondary education.

Since 1996, Peru has allowed for-profit provision in education, leading to a rapid expansion of private institutions at both the secondary and post-secondary levels. Approximately one-quarter of high school students attend private schools, although in urban areas this share ranges from 50 to 70 percent. The private school sector is highly heterogeneous, comprising a small number of elite institutions alongside many low-cost schools, with enrollment largely determined by household wealth and geographic proximity. In both public and private schools, each grade is generally divided into several sections. Students within the same section form close-knit social networks, usually advancing together from the first to the final year of high school and taking all their classes as a group. This structure fosters friendships that are predominantly formed within the section. Each section has a head teacher, or "tutor," who interacts closely with all students and provides advice on academic matters as well as future educational and career choices.

Public and private universities coexist. Following a nationwide accreditation process completed in 2020, licenses were denied to two public and 46 private universities, about roughly half of all institutions operating at the time. There are currently around 100 universities in Peru, about half of which are public, yet approximately 70 percent of university students are enrolled in private institutions. University admissions in Peru are decentralized, with each institution administering its own entrance examination. The admissions process usually takes place between September and March, and the academic year typically begins in late March. Public universities charge no tuition but are generally more selective; admission thresholds vary across fields of study. Private universities vary substantially in quality and admission standards but are generally less competitive than public universities. Geographic proximity to a post-secondary institution plays an important role in students' university choices, particularly among women (Alba-Vivar, 2025).[9]

While STEM careers in Peru encompass various disciplines, engineering overwhelmingly dominates students' STEM choices. In 2016–2017, roughly 93% of the 417,000 applicants to STEM programs applied to engineering majors. As in many countries in Latin America and elsewhere, female participation in STEM—and in engineering in particular—remains low. During that period, only 30% of STEM applicants were women,[10] and just 19% of female applicants nationwide chose

[9] After graduating from high school, students may also enroll in two-year technical institutes, which are mostly private and offer vocational training without a pathway to a university degree.

[10] STEM fields include Biology, Mathematics, Statistics, Engineering, Physics, Chemistry and Architecture. Medicine and related health sciences are excluded from this classification; in medical programs, women are the majority, representing about 70% of enrolled students.

engineering as their intended major, compared to 46% of male applicants. The gender gap is even more apparent when looking at enrollment and graduation rates. Recent OECD data reveal that only 9% of women as opposed to 29% of men entered college to pursue a Bachelor degree engineering in 2023, the latest year with data availability and the year of our intervention.[11]

Our study involves high schools located in six northern regions of Peru: Piura, La Libertad, Cajamarca, Ancash, Lambayeque, and Tumbes. The Piura region accounts for about 65 percent of the sample schools. Secondary school enrollment in our study area is approximately 96.3%, close to the national average of 97%. Moreover, 50.2% of high school students in our sample are in the grade level corresponding to their age, slightly below the national average of 52.8%. In terms of post-secondary education, college enrollment among individuals aged 17–24 in the study regions is around 31.5%, below both the national average of 33% and the coastal-region average of about 35%.[12]

3 The Instagram Intervention

We recruited 73 high schools from 6 regions of Northern Peru to participate in the study. This was made possible by the ongoing relationship between high schools and the Universidad de Piura (the home base of one of the authors). We randomly selected two thirds of the schools to receive the Instagram intervention. Of them, half also received an add-on information intervention targeting the head teacher of the graduating class. The school-level randomization was stratified by municipality, by whether the school was co-ed or girls-only (about 86 percent of schools in the sample are co-ed), and by the Socio-Economic status (*high or low*) assigned to the school by the Universidad de Piura.

3.1 Design

The Instagram intervention involved the creation of an account designed to showcase the daily lives of women studying engineering in college. Girls in the treatment group were invited to follow the account and engage with the content, which was posted weekly over a six-week period. The account was managed by six female engineering students at the Universidad de Piura, who designed the logo (see Figure 1) and produced short video reels – typically 5 to 10 seconds long – depicting their

[11] The OECD data can be downloaed here: https://gpseducation.oecd.org/CountryProfile?primaryCountry=PER&treshold=5&topic=EO

[12] Fuente: INEI – *Indicadores de educación según departamentos*, 2013–2023. https://cdn.www.gob.pe/uploads/document/file/7043096/6061323-peru-indicadores-de-educacion-segun-departamentos-2013-2023.pdf?v=1728072117

experiences on campus. The role models were all from the northern region of Peru, making them relatable to the targeted high school students.

The reels followed the typical Instagram format, incorporating music and humorous or eye-catching text. To encourage engagement, participants who liked the content were eligible for small lottery prizes (e.g., a small purse or headphones), mirroring strategies commonly used by Instagram influencers. Importantly, the role models were given full creative freedom to decide what content to create and share in order to inspire high school students to follow in their footsteps. Some reels featured photos of and references to female scientists who had influenced the students' academic journeys. Others showed scenes of campus life, such as walking through university buildings, studying alongside other women, taking exams, and discussing coursework with professors. The overall goal was to present relatable peer role models from similar backgrounds, inspire high school viewers, and make college life, particularly in engineering, appear more accessible, enjoyable, and compatible with their identities.

We designed the intervention to influence girls' educational choices through several complementary mechanisms. By documenting everyday college life, the Instagram content aimed to provide information about university life, engineering studies, and the presence of women in STEM. By featuring relatable female engineering students, it sought to strengthen girls' confidence in their ability to succeed in higher education and engineering in particular. Finally, by encouraging repeated engagement with the account over six weeks, the intervention was designed to reinforce these messages over time. The Instagram's recommendation algorithm may have further reinforced the content shared on the account, by directing participants to similar content and creators. Over the longer run, the intervention could also generate peer effects, both on and off the platform, if treated girls shared content, affected the content shown to their friends on Instagram, or influenced their peers' educational aspirations and choices through changes in their own behavior.

In half of the treatment schools we also implemented an intervention targeting the head teachers of the graduating class. Specifically, we sent these teachers three short videos (each approximately 30 seconds long) via WhatsApp, featuring three engineering professors – two women and one man – speaking directly to teachers. In their messages, the professors emphasized the under-representation of women in engineering, affirmed the capabilities of women to succeed in the field, and encouraged teachers to actively support and motivate more girls to pursue engineering studies. Since we find no significant differences between the two treatment arms, we present pooled treatment effects throughout the paper and report separate estimates in the Appendix.

3.2 Implementation

The Instagram account was promoted by the head teachers of final years students in the treatment group during school hours. Its handle was posted in class on the board, and head teachers encouraged girls to follow the account. The intervention was implemented over a six-week period in September and October 2023, during which nine videos were posted by the participating college students. In order to avoid contamination of the control group, the account was set as private and only girls assigned to the treatment group were provided access, if they requested. This was made possible by the implementation of the baseline survey before the intervention. Nearly 90 percent of the surveyed girls had an Instagram account at baseline.[13] This allowed the account managers to verify the treatment-group nature of the girls requesting access to the account. Any possible requests coming from boys were also rejected.

During the six-week intervention period, the role models shared nine reels documenting their experiences, twelve posts with photos, and additional posts designed to encourage engagement. The account remained active after the 6 weeks, but no additional posts were made.

4 Data and Estimation Strategy

In July 2023, we implemented a baseline online survey of final-year students in all sampled high schools. The survey was promoted in class by teachers, who provided students with the survey link. It collected information on students' educational aspirations and expectations, beliefs about their parents' educational preferences, perceived support from teachers, prior-year final grades in math and language, and confidence in their own math abilities. The survey also elicited beliefs about the educational plans and college-going likelihood of students' three closest friends, as well as measures of gender attitudes and self-efficacy. Importantly, participation required students to provide their national ID number, enabling us to track their post-secondary enrollment using administrative records. Since all study participants were minors, both student assent and parental consent were obtained prior to participation. This led to a sample size of 547 girls, which correspond to about 15 percent of the graduating class in the sampled schools.

At the end of the program implementation, in mid-October 2023, we invited all students in the study sample to complete a follow-up survey, using the same implementation strategy as at baseline, i.e., promotion by teachers in class and access via an online link. When implementing the follow-up

[13] If they did not have an account, they were invited to create one and provide the handle.

survey, only the 547 study participants who had consented at baseline were invited to fill it in. A total of 495 girls responded, i.e., 90 percent of the original sample, with no significant differences in response rates across treatment arms.[14]

Approximately two months after the follow-up survey, toward the end of the academic school year in December 2023, we announced a small scholarship program targeting students planning to pursue engineering in college. Specifically, we informed the sampled schools that two scholarships—one for a girl and one for a boy—would be randomly awarded among eligible applicants. To qualify, students were required to submit a brief application by early January 2024 and subsequently enroll in an engineering program in the following academic year. The scholarship program was designed to provide a revealed-preference measure of students' interest in studying since applying required an active commitment and was linked to subsequent enrollment in an engineering degree.

Finally, for each student surveyed at baseline, we obtained college enrollment data from the Education Ministry in December 2024, one year after the students' high school graduation.

This data collection process led to our pre-registered outcomes of interest. Short-term outcomes are self-stated *preferences for the engineering major* as generated by the follow-up survey and scholarship application. Longer-term outcomes are enrollment in engineering in college and, more broadly, college enrollment.

In addition to the girls' sample, we also collected survey data from a sample of 240 boys attending the same (co-ed) schools. Of these, 212 boys (88 percent) completed the follow-up survey. As with the girls, we obtained administrative data on scholarship applications (which were open to both boys and girls) and college enrollment for the full sample of 240 boys. We use the boys' sample both to document gender gaps in educational preferences within this context and as a placebo test, since the interventions were designed to target girls exclusively.

4.1 Estimation Strategy

Given the stratified school-level randomization and the individual-level nature of the outcomes of interest, we test for the impacts of the *Instagram (T1)* and the *Instagram & WhatsApp (T2)* intervention by estimating the following equation:

$$Y_{is} = \alpha + \beta T_s + \gamma SES_s + \delta Coed_s + \lambda_s + \zeta \mathbf{X}is + \epsilon is, \tag{1}$$

[14] See Table A1 in Appendix.

where Y_{is} represents the outcome for student i in school s, and T_s is an indicator equal to one if school s was assigned to the treatment group. We always control for the variables used to stratify the randomization: an indicator for the school being co-ed, an indicator for the school being categorized as low Socio-Economic Status (SES), and municipality fixed effects λ_s. In the most comprehensive specification, we control for child characteristics X, selected for each outcome through a Double Lasso procedure (Belloni et al., 2014), out of a large set of covariates measured at baseline.[15] When the outcome of interest is a survey measure elicited at endline, X_{is} also includes the corresponding variable measured at baseline. Standard errors are clustered at the school level, our unit of randomization. Since we have four primary outcomes of interest, two obtained in the short- and medium-term through survey and scholarship application, and two obtained a year post graduation from administrative data on college enrollment, we correct for multiple hypothesis testing by employing the Romano-Wolf step-down procedure (Romano and Wolf, 2005).

The main analysis is restricted to female students, since they were targeted by the Instagram intervention. However, since we have collected data also for a subset of boys in the sampled schools, we also replicate the analysis for the pooled sample, while including a gender dummy and its interaction with the treatment indicator. We report the resulting estimates in the Appendix. Estimates generated when separating the Instagram-only and Instagram-plus-WhatsApp interventions are also reported in the Appendix.

We expect the impact of the interventions on interest in the economics major to vary by girls' math abilities. Therefore, following our pre-registration, we examining heterogeneous impacts by math aptitude by estimating the following equation:

$$Y_{is} = \alpha + \beta_1 T_s + \beta_2 T_s \times TopMath_i + \beta_3 TopMath_i + \gamma SES_s + \delta Coed_s + \lambda_s + \zeta \mathbf{X}is + \epsilon is, \quad (2)$$

where *TopMath* is a 0-1 indicator equal to 1 if the student received top grades in math at the end of the previous semester, i.e., a grade of 19 or 20, out of 20.[16] In this specification, β_1 captures the treatment effect for girls who did not receive top grades in mathematics, while $\beta_1 + \beta_2$ gives the corresponding treatment effect for top-performing girls. As in the main analysis, we report

[15] The Double Lasso method performs two separate Lasso regressions, one regression of the outcome on all covariates to identify relevant predictors of the outcome, and another regression of the treatment on all covariates to identify predictors of the treatment. It then takes the union of the selected covariates from both regressions as the control vector.

[16] This corresponds to the top quantile of the grade distribution.

pooled treatment effects. Estimates separately comparing the Instagram-only and Instagram-plus-WhatsApp interventions are reported in the Appendix.

We employ the same empirical strategy when conducting our analysis of possible mechanisms. We also conduct exploratory (not pre-registered) analyses of treatment effect heterogeneity by students' predicted probability of enrolling in college in the absence of the intervention.

5 Results

5.1 Balance Tests and Treatment Take-up

We present descriptive statistics of the schools involved in the study in Table 1 and of the sampled girls in Table 2. The vast majority of the schools are co-ed, with similar proportions across groups. The groups are also balanced in terms of student-teacher ratios, which average around 17 across all arms, and in the proportion of students who are girls. Schools in the sample enroll between 400 and 500 students on average, with graduating cohorts ranging from 80 to 100 students. On average, each school has approximately 50 girls in their final year of high school, of whom between 13 and 20 percent participated in our study. The treatment group contains a larger share of schools classified as low socioeconomic status (71% versus 56%).

The baseline characteristics of the surveyed girls are also well balanced across treatment arms (Table 2), with very few statistically significant differences. On average, girls are just over 16 years old, fewer than one-third have a parent with a college degree, and more nearly all of them state that they aspire to attend college. However, only half of them are confident that they could successfully complete college. About 13 percent would like to study engineering in college. Confidence in math ability is low, with less than one third of girls believing that they are in the top half of the class based on their math performance. Finally, nearly 90 percent of girls had an Instagram account at baseline, and almost half reported spending more than two hours per day on social media, confirming that Instagram provided a natural platform for the intervention.

When comparing girls' survey answers to those of boys, we observe significant gender gaps across several dimensions. Although academic performance in math and language is similar across genders, boys report significantly higher levels of confidence. Nearly 58 percent of boys believe they are among the top half of math performers in their class, compared to just 29 percent of girls. Similarly, 42 percent of boys believe they are among the top 20 percent of math performers, compared to 24 percent of girls. The gender gap is even larger when considering confidence in

pursuing engineering: on a scale from 1 to 5, boys report average confidence levels of 3.65 and 3.44 for industrial and mechanical engineering, respectively, compared with 3.00 and 2.63 among girls.[17] Finally, boys are less likely to have an Instagram account and spend less time than girls on social media.

Overall, 29 percent of girls in the treatment group followed the Instagram account, as shown in Table A2. Conditional on following the account, engagement was substantial: participants liked an average of 7.5 posts and 2.7 reels, while 63 percent liked at least one post and 58 percent liked at least one reel. Looking at the full treatment sample, including girls who did not follow the account, participants liked an average of 2.2 posts and 0.8 reels, with about one in five girls liking at least one post or reel. None of the engagement measures differs significantly between the two treatment arms, suggesting that the teacher add-on intervention did not affect girls' engagement with the Instagram content.

When examining the determinants of selection into the Instagram account within the treatment group (Appendix Table A3), we find no evidence that take-up or engagement differed by girls' demographics, baseline aspirations to attend college, or interest in engineering. The only significant predictors of engagement are having an Instagram account at baseline and spending substantial time on social media. Specifically, girls who already had an Instagram handle at baseline were substantially more likely to follow the account and to interact with its content, while those reporting more than two hours of daily social media use tended to like fewer reels and posts, possibly because they were exposed to a larger volume of competing content on social media.

5.2 Treatment Impacts on Education Preferences and Choices

Column 1 to 4 of Table 3 and panel (a) of Figure 2 report the estimated intent-to-treat impacts on girls' self-reported interest in engineering and scholarship applications. Table 4 presents estimates from our pre-registered heterogeneity analysis by top performance in math. Our estimates indicate that the social media interventions had an immediate negative effect on girls' self-reported interest in pursuing an engineering major. This effect is statistically significant among girls who are not top performers in math. By contrast, there is no impact on scholarship applications in the full sample and among non-top girls, but a large positive impact among top-performing girls, whose likelihood of applying for the scholarship more than doubles.

[17] We also see that boys exhibit more regressive gender attitudes on average (with more negative standardized scores) and significantly higher levels of self-efficacy. See Appendix Table A4 for boys' characteristics.

The estimates for college enrollment indicate no effects on engineering enrollment, which remains low, at less than 7 percent (4.5 percent for non-top performing girls and 16.7 percent for top-performing girls). However, we find a large and statistically significant impact of the Instagram intervention on college enrollment regardless of major, as shown in the bottom right panel of Figure 2 and columns 7 and 8 of Tables 3 and 4. Specifically, the Instagram intervention led to a 14.9 percentage point increase in college enrollment (a 56 percent increase over the control mean of 26.5 percent), with the impacts being signifcant both for non-top (13.9 percentage point increase) and top-performing students (20 percentage point increase). The estimated treatment effects are robust to the inclusion of Double Lasso controls and to correcting p-values for multiple hypothesis testing.

While we do not find evidence of treatment effects on engineering enrollment, we do find that the Instagram intervention shifted girls toward other STEM fields. As shown in Figure 3 and Table 5, the intervention increased enrollment in non-engineering STEM majors[18] by 4 percentage points in the full sample. Heterogeneity analysis by math performance at baseline show that the impact on top girls is particularly large (11.3 percentage points) and highly statistically significant. We also find a significant increase in law enrollment among top-performing girls (law is an undergraduate major in Peru). Among non-top-performing girls, we find suggestive evidence of increases in enrollment in non-engineering STEM (2.4 percentage points), medical and health sciences (3.7 percentage points), and humanities (3.5 percentage points), although these estimates do not reach conventional levels of statistical significance (p-values between 0.12 and 0.16).

We conduct several additional analyses to assess the robustness of our primary findings. First, we examine whether the intervention affected boys attending the same schools. This could be seen as a placebo test, since boys were neither targeted by the intervention nor able to access the Instagram account. When estimating heterogeneous effects by student gender, we find null impacts among boys for all variables of interest, as shown in Table A5 in Appendix.

Second, we estimate school-level analyses to verify that the results are not driven by a small number of outlier schools. We begin by examining the distribution of college-going surveyed students across schools, by treatment. Figure 4 shows a clear rightward shift in both the number and the percentage of college-going girls in treatment schools. We then estimate school-level Poisson regressions, which allows us to examine the effects of the intervention on the number of girls in each school who (i) expressed a preference for an engineering major, (ii) applied for the scholarship, (iii) enrolled in an engineering program, and (iv) enrolled in college, as shown in Table 6. In the

[18]The non-STEM majors in our data are: math, statistics, biology, chemistry, architecture, and aerospace studies.

even-numbered columns, we include an exposure (offset) term equal to the number of surveyed girls in each school, to account for differences in school sample size and estimate impacts on the corresponding rates rather than raw counts. In the exposure-corrected specification, the coefficient of 0.509 obtained for the number of girls who enrolled in college implies a 66 percent increase in the college enrollment rate, corresponding to approximately 17.6 percentage points relative to the control mean of 26.5 percent.[19]

An important question is whether the increase in college enrollment was driven primarily by enrollment at specific institutions, particularly the university featured in the Instagram account (the Universidad de Piura - a high quality private institution), or whether it extended to other institutions. We therefore begin by examining enrollment at this university. Although the estimated treatment effects are positive, they are not statistically significant (Appendix Table A8), suggesting that the intervention did not simply encourage girls to enroll at the institution represented by the role models. Next, we distinguish between public and private universities. The former are generally more selective and higher quality than private universities, although the latter may vary quite considerably in quality. We find positive and statistically significant effects on enrollment in both sectors, with enrollment in public universities increasing by 5 percentage points (over a control mean of 6.6 percent) and enrollment in private institutions increasing by 10 percentage points (over a mean of 21 percent), as shown in Appendix Table A9. This suggests that the intervention increased college attendance more broadly rather than redirecting students toward a particular type of institution.

Finally, we classify institutions according to their quality using widely used university rankings. Specifically, we distinguish between high- and medium-quality institutions and lower-quality institutions. As shown in Table A10 in Appendix, the intervention increased enrollment in both categories. The estimated point estimate is somewhat larger for higher-quality institutions but percentage wise larger for lower quality institutions. Overall, this analysis suggests that the intervention encouraged girls to pursue higher education across the quality distribution.

5.3 The Teacher Intervention Add-on

When estimating the effects of the Instagram intervention alone (T1) separately from the combined Instagram and teacher WhatsApp intervention (T2), we obtain broadly similar results, with no

[19] Dropping the two treatment schools that sent more than 10 girls to college yields a coefficient of 0.432 in the exposure-corrected Poisson specification, corresponding to an estimated 54 percent increase in the college enrollment rate; this is approximately a 14 percentage point increase relative to the control mean of 26.5 percent, and very close to our student-level estimates.

statistically significant differences between the two treatment arms in the full sample, as shown in Figure A1 and Table A6 in Appendix. However, the heterogeneity analysis by math performance reveals suggestive differences between T1 and T2. Among non-top-performing girls, the positive effect of the Instagram intervention on college enrollment is driven primarily by T1 and becomes smaller and statistically insignificant when the teacher intervention is added. By contrast, among top-performing girls, the positive impacts on scholarship applications and college enrollment are concentrated in T2, suggesting that the teacher intervention reinforced the effects of the Instagram campaign for academically stronger students. This pattern suggests that when teachers were encouraged to advise high-achieving girls to pursue engineering studies, they may have reallocated their advising and encouragement efforts toward top-performing students. As a result, non-top-performing girls may have received less encouragement to pursue higher education or may have been advised that college was a less suitable option for them.

5.4 Possible Mechanisms

We pre-registered two sets of secondary outcomes to help shed light on the mechanisms underlying the treatment effects: (1) students' confidence, and (2) their perceptions of parental and teacher support for post-secondary education. Regarding confidence, our original plan was to measure students' confidence in their math ability. However, when finalizing the follow-up survey, we concluded that the interventions were more likely to affect confidence in going to college, particularly to study engineering. We therefore asked students how confident they were in their ability to complete a college degree, as well as degrees in mechanical engineering, industrial engineering, law, economics or business, medicine, and education. To measure perceived parental preferences, we asked whether students believed their parents wanted them to attend college and, if so, which major they preferred. To capture teacher support, we asked whether students had discussed college with a teacher and, if so, which major the teacher most strongly recommended, with particular attention to engineering.

When finalizing the follow-up survey, we decided to also measure students' beliefs about their best friends' post-secondary educational choices. To do so, we asked each student to name their three closest friends and, for each one, report whether they believed that friend would attend college and, if so, what major they would pursue. Our key outcomes in this domain are: (1) the number of friends (out of three) whom the respondent believes will go to college, and (2) among those friends expected to attend college, the number believed to be pursuing an engineering degree.[20]

[20]These measures are not pre-registered.

The top panel of Figure 6 reports the estimated impacts of the Instagram intervention on self-reported confidence in ability to complete college and to complete engineering degrees, measures as a 0-1 dummy equal to 1 if the student answered "yes definitely" to the question: "Do you believe that you have the academic aptitude and abilities to complete a college degree/a college degree in mechanical engineering/ a college degree in industrial engineering?." In line with our primary results for college enrollment, we find evidence of significant positive impacts on confidence in the ability to complete college, but no impacts on confidence in ability to complete a mechanical or industrial engineering degree.[21] The bottom panel of Figure 6 show evidence of positive treatment effects (albeit small) on students' perceptions of their peers' educational aspirations. Specifically, students exposed to either intervention were more likely to believe that their close friends would go to college. This is driven by not top-in-math, girls. Additional analyses (Table A7 in Appendix) show no impacts on girls' beliefs about their parents' preferences, either regarding college attendance or the pursuit of engineering, and on students' perceptions of teacher's support.

5.5 Exploratory Analysis: Baseline Probability of Going to College

Given the large impacts of the intervention on college enrollment, we conduct an explorative analysis, following Dynarski et al. (2021), to assess whether the observed increase in college enrollment is concentrated among students with high baseline enrollment prospects or whether the intervention increased college attendance among girls who were initially less likely to pursue higher education. To do so, we first estimate an OLS model using only control-group observations, where the dependent variable is an indicator for college enrollment and the explanatory variables are the baseline characteristics reported in Table 2. We then use the estimated coefficients to predict each student's probability of college enrollment, which serves as a proxy for baseline propensity to attend college in the absence of the intervention.[22]

Figure 5 plots treatment and control outcomes against this predicted probability. We partition students into ten equally sized groups (deciles) according to their predicted probability of college

[21] We also do not find robust evidence of impacts of completing other college degrees. When distinguishing between the Instagram treatment arms (with and without the teacher add-on), we find that the Instagram intervention alone (T1) significantly increases confidence in completing college, particularly among non-top-performing girls, whereas this effect disappears under the combined Instagram and teacher intervention (T2), a pattern consistent with teachers shifting their support toward top-performing students.

[22] We also conduct exploratory analyses of heterogeneous treatment effects by two measures of students' socioeconomic background: parental education and the socioeconomic classification of their high school. These analyses provide no evidence of meaningful heterogeneity in treatment effects. The main results are observed for both first-generation and continuing-generation college students, as well as for students attending both low- and high-socioeconomic-status schools.

enrollment.[23] Each point represents the mean outcome within a decile, and quadratic functions are fitted separately for the treatment and control groups. The vertical bars denote 95 percent confidence intervals. Panel (a) of Figure 5 suggests that the negative effect of the Instagram intervention on preferences for the engineering major is concentrated among girls with the lowest predicted probability of college enrollment. Conversely, panel (d) suggests that the positive impacts on college enrollment are concentrated among girls in the bottom tercile of the predicted probability distribution. The differences between treatment groups become progressively smaller as the predicted probability of college enrollment increases. This is confirmed by regression analysis where we include indicators for medium and top tercile, interacted with the Instagram treatment dummy . The estimated treatment effect on engineering preferences (survey-based) is statistically significant and negative for girls' becomes smaller for girls in the middle tercile and becomes positive and not significant for the girls in the top tercile, as shown in Appendix Table A11. Similarly, the coefficient obtained for college enrollment is large (27.3 percentage points) and highly significant for the girls in the bottom tercile, while the interaction terms are both negative, implying smaller effects among girls with higher baseline probabilities of college enrollment. The treatment effect remains statistically significant for the middle tercile (18.2 percentage points; $p = 0.049$), but is close to zero and statistically insignificant for the top tercile (3.5 percentage points; $p = 0.621$).

This analysis sheds some light on the negative effects of the intervention on engineering preferences measured immediately after the Instagram campaign. The results suggest that these negative effects are concentrated among girls who, based on their baseline characteristics, were least likely to attend college in the absence of the intervention. These same girls are the ones more impacted in their likelihood to enroll in college. One possible interpretation is that the intervention's emphasis on engineering led girls with the lowest baseline probability of attending college to perceive engineering as particularly demanding or beyond their reach. Rather than reducing their aspirations for higher education more generally, the intervention seems to have discouraged interest in engineering among these girls while encouraging them to consider college through other fields of study.

6 Discussion and Conclusion

Through a randomized controlled trial in Northern Peru, we evaluated the impact of a role model intervention delivered via Instagram. The primary aim was to inspire more girls in their final year of

[23] Dynarski et al. (2021) used ventiles but our sample size is too small for a similar partitioning.

high school to consider and pursue STEM fields, and engineering in particular. Overall, our findings indicate that information interventions targeting teenagers via heavily used social media platform can meaningully impact education preferences and choices.

Although the intervention did not increase enrollment in engineering programs, it substantially increased overall college attendance one year after high school graduation, and led students - particularly top-performing girls - to enroll in non-engineering STEM majors. Our analysis of mechanisms suggests that increased confidence in attending college and changes in beliefs about peers' educational trajectories contributed to these effects. Girls exposed to the intervention became more confident in their ability to complete college and were more likely to believe that their best friends would also pursue higher education.

While the intervention initially reduced self-reported interest in engineering, our analysis of heterogeneous effects indicates that this decline was concentrated among girls who were least likely to attend college, suggesting that these students may have been discouraged by the intervention's strong emphasis on engineering, a field they perceived as particularly demanding or beyond their reach. At the same time, top-performing girls became more likely to apply for an engineering scholarship, indicating that the intervention successfully encouraged students with the strongest academic preparation to consider the engineering major. This, together with the treatment impacts on non-engineering STEM majors, particularly among top-performing girls, suggests that these girls may have become more interested in engineering as a result of the intervention but ultimately switched to related fields, such as architecture, either because they felt more confident in their ability to succeed in those fields than in engineering (consistent with our finding that the intervention did not increase confidence in pursuing an engineering degree) or because they did not meet the high admission thresholds for engineering.

The treatment effects we observe on college enrollment are strikingly large and robust. One plausible explanation for the observed effect sizes is that Instagram's recommendation algorithm reinforced the intervention and amplified its impacts. Once students began engaging with the role model content, Instagram's recommendation algorithm may have exposed them (and possibly their friends) to additional, similar content, such as videos and accounts created by other young women documenting their college experiences, creating a positive feedback loop between students' own aspirations, peer dynamics, and the broader digital environment they navigate daily. While our data do not allow us to identify these amplification effects, they provide a plausible explanation for why a relatively short social media campaign generated lasting changes in educational behavior.

Overall, our study highlights the promise of social media as a tool for education interventions. Our findings suggest that reaching and inspiring teenage girls through heavily used social media platforms may be easier and more impactful than previously thought. Compared with traditional ways of delivering information and role model interventions, social media platforms such as Instagram can reach large numbers of young people at low cost while presenting information in a more familiar and engaging way. Moreover, recommendation algorithms and online peer networks may reinforce the intervention content beyond the initial messages. As internet access and smartphone penetration continue to grow worldwide, social media platforms offer a scalable and cost-effective way of reaching adolescents, particularly those who might otherwise lack access to role models, counseling, or institutional guidance.

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Figures and Tables

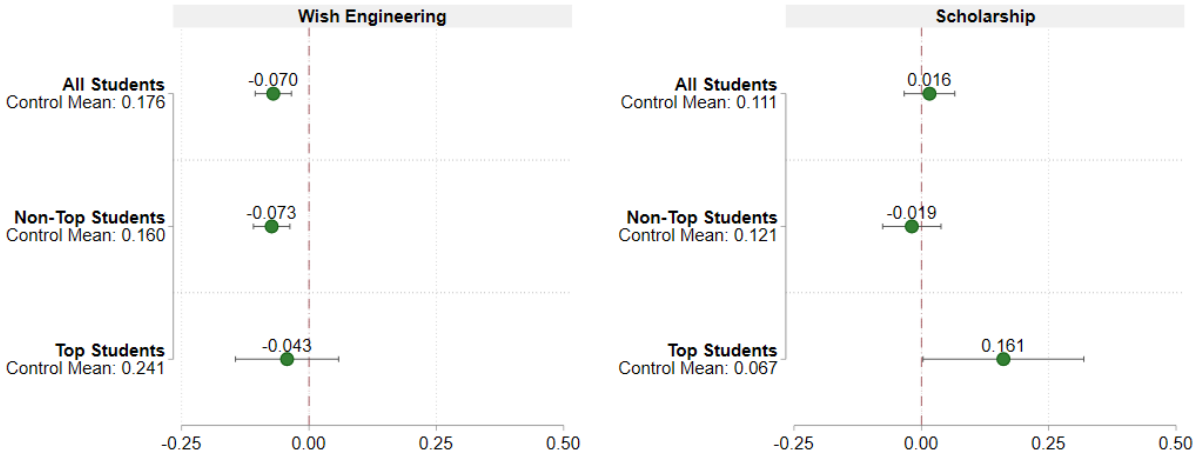
Figure 1: The Instagram Account



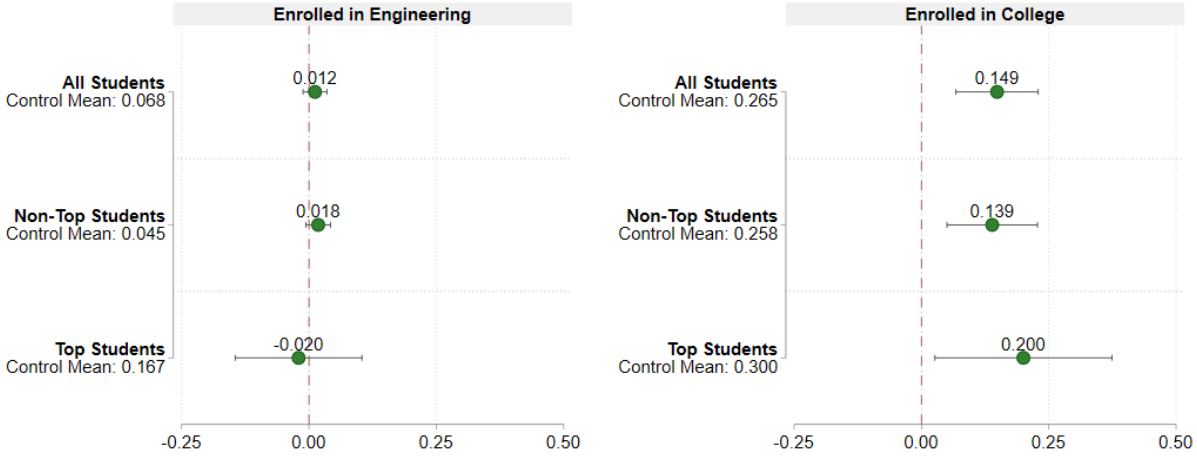
Note: The figure displays the Instagram account logo and name, as well as the first post (on the left), which states: " We are a group of university students and we are excited to share our life in university with you. Stay tuned to learn about our experiences, academic advice and special moments that make this stage unforgettable."

Figure 2: Treatment Impacts on Education Preferences and Choices

(a) Short-term Outcomes

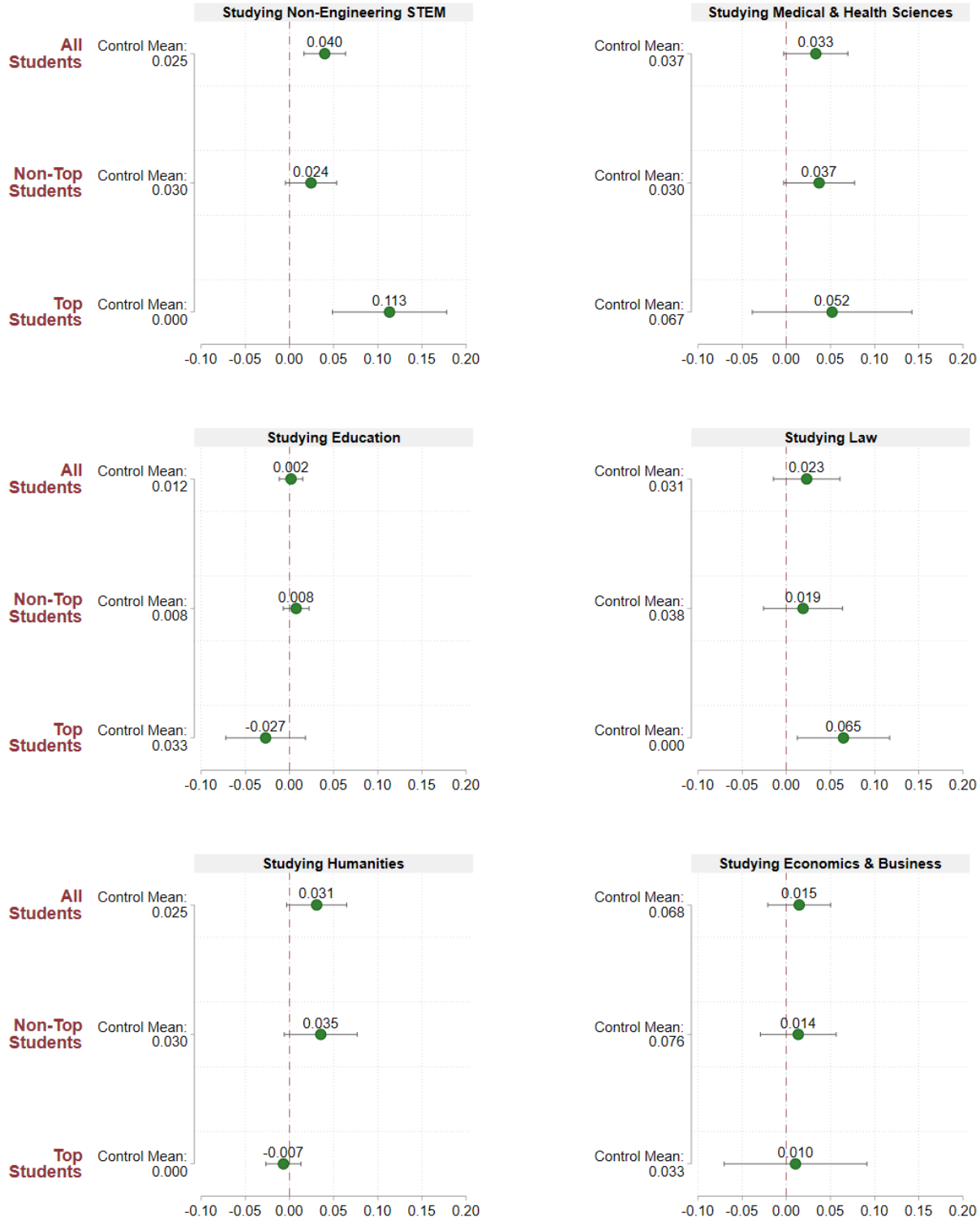


(b) Longer-term Outcomes



Notes: The figure reports estimated coefficients and 95% confidence intervals generated by regression analyses reported in the even columns of Tables 3 ad 4. "Wish engineering" is a 0-1 indicator equal to 1 if the student stated that engineering is her desired field of study in college. "Scholarship" is a 0-1 indicator, equal to 1 if the student applied for the engineering scholarship that we created about 3 months after the intervention. "Enrolled in Engineering" is a 0-1 indicator, equal to 1 if the student is enrolled in college and studying engineering 1 year after graduating high school, and 0 otherwise. "Enrolled in college" is a 0-1 indicator, equal to 1 if the student is enrolled in college 1 year after graduating high school (regardless of major), and 0 otherwise. Controls are selected through the Double Lasso procedure from the set of variables displayed in Table 2, and always include the randomization strata: school-level indicators for low SES status, and co-educational status, in addition to metropolitan area fixed effects.

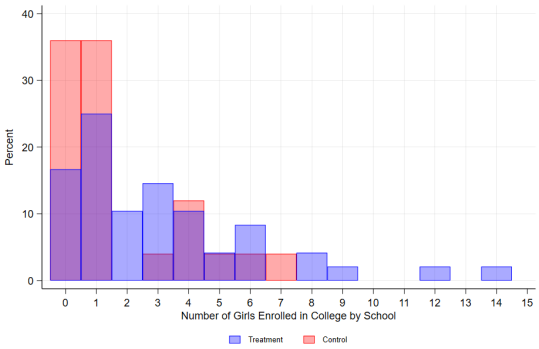
Figure 3: Treatment Impacts on Enrollment in Other Fields



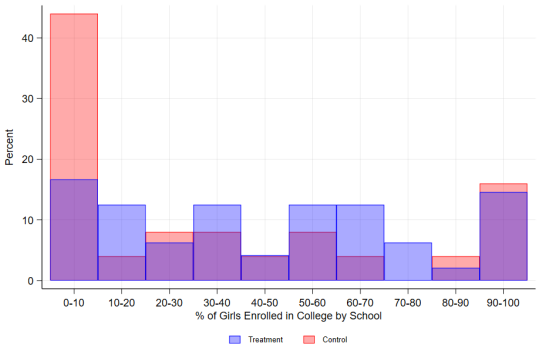
Notes: The figures report ITT coefficient estimates and 95% confidence intervals linear probability models. In each panel, the dependent variables is a 0-1 indicator, which is equal to 1 if the student is enrolled in college pursuing the corresponding major, and 0 otherwise. Controls are selected through the Double Lasso procedure from the set of variables displayed in Table 2, and always include the randomization strata: school-level indicators for low SES status, and co-educational status, in addition to metropolitan area fixed effects.

Figure 4: School-level Distribution of College-Going Girls

(a) Number of Surveyed Girls



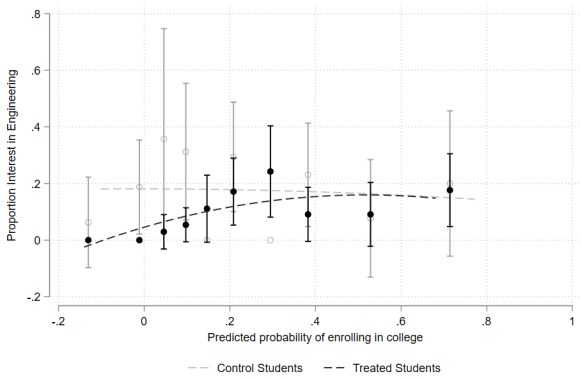
(b) Percentage of Surveyed Girls



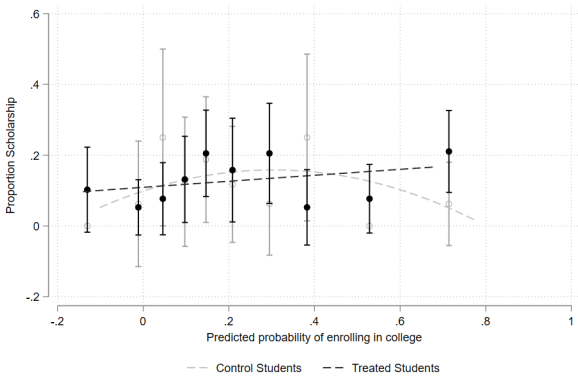
Note: The figures displays the percentages of Treatment and Control school with the corresponding number (panel a) or percentage (panel b) of surveyed girls enrolled in college one year after their high school graduation.

Figure 5: Heterogeneity by Predicted Probability of University Enrollment

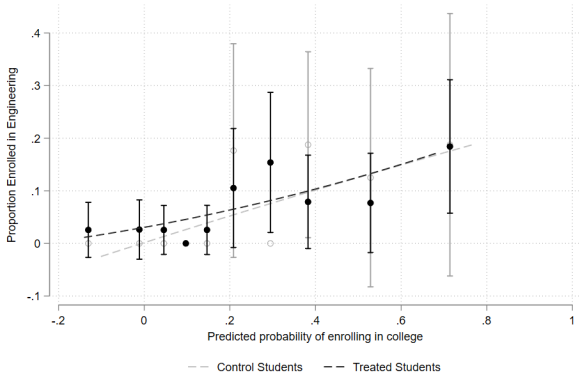
(a) Interest in Engineering



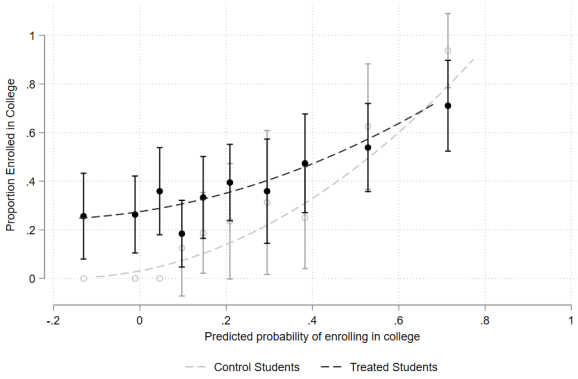
(b) Scholarship Application



(c) Enrollment in Engineering

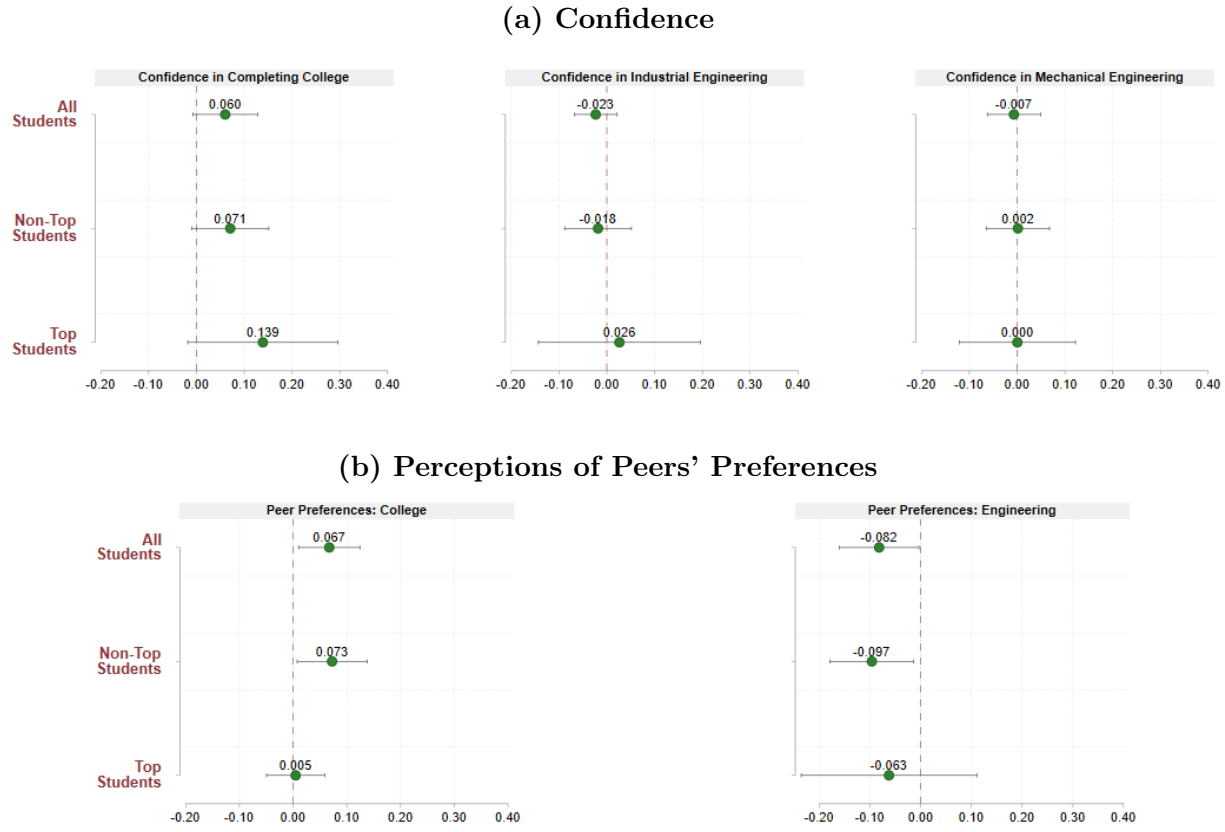


(d) College Enrollment



Notes: The figures plot mean outcomes against students' predicted probability of college enrollment, estimated using an OLS model fitted on the control group with the baseline characteristics reported in Table 2. Students are grouped into ten equally sized bins (deciles) based on their predicted probability. Each point represents the mean outcome within a decile for the treatment or control group. The fitted curves are quadratic regressions estimated separately by treatment status. Vertical bars denote 95 percent confidence intervals.

Figure 6: Mechanisms: Estimated Impacts on Confidence and Perceived Peers' Preferences



Notes: In panel (a), The figures report ITT coefficient estimates and 95% confidence intervals linear probability models. In all columns of panel (a), the dependent variables are 0-1 indicators for the student having answers "definitely yes" to an endline question asking if they believed they had the ability to complete college (top left), complete a degree in Industrial Engineering (top middle), complete a degree in Mechanical Engineering (top right). In panel (b), the figures report ITT coefficient estimates and 95% confidence intervals OLS regressions. To measure perceptions of peers' preferences for college and for engineering, we asked students to list and name their three best friends. We then asked if each friend would go to college after graduation, and, if so, what their field of study will be. The outcome variable in column 1 is the number of friends, out of 3, who the student thinks will go to college. The outcome of variable in column 2 is the number of friends, out of 3, whom the student thinks will study engineering. Controls are selected through the Double Lasso procedure from the set of variables displayed in Table 2, and always include the randomization strata: school-level indicators for low SES status, and co-educational status, in addition to metropolitan area fixed effects.

Table 1: School Balance Table

	Control	Treatment	C=T
Co-ed	0.84	0.85	0.875
	(0.37)	(0.36)	
Low SES	0.56	0.71	0.210
	(0.51)	(0.46)	
Private	0.72	0.69	0.778
	(0.46)	(0.47)	
Total Students	388.92	461.71	0.464
	(374.58)	(414.25)	
Student/Teacher Ratio	17.93	17.23	0.735
	(8.49)	(8.20)	
Perc. Female Teachers	0.47	0.39	0.096
	(0.23)	(0.16)	
Total Final-Year Boys	28.00	42.44	0.265
	(24.11)	(61.62)	
Total Final-Year Girls	50.12	48.62	0.916
	(76.17)	(44.37)	
Perc. Final-Year Girls	0.54	0.54	0.917
	(0.24)	(0.21)	
Average Number of Boys Surveyed	3.08	3.40	0.713
	(3.28)	(3.56)	
Average Number of Girls Surveyed	6.48	8.02	0.424
	(6.60)	(8.31)	
Observations	25	48	

Notes: The table reports average school characteristics, by treatment assignment. For each variable, the p-values reported in column 3 are generated by tests of equality between the two groups.

Table 2: Balance Table - Girls

	Control	Treatment	C=T
Panel A: Demographics			
Age	16.07	16.17	0.016
	(0.45)	(0.40)	
Mom Went to College	0.30	0.29	0.900
	(0.46)	(0.45)	
Dad Went to College	0.33	0.29	0.334
	(0.47)	(0.45)	
Math Performance	16.55	16.53	0.919
	(2.22)	(1.96)	
Language Performance	17.33	17.26	0.688
	(1.78)	(1.60)	
Top Math Student	0.19	0.14	0.158
	(0.39)	(0.34)	
Wish College	0.99	0.96	0.081
	(0.11)	(0.20)	
Wish Engineering	0.14	0.12	0.583
	(0.35)	(0.33)	
Wish STEM	0.17	0.14	0.291
	(0.38)	(0.34)	
Panel B: Self-Reported Confidence			
Thinks she is Top 50% in Math	0.32	0.29	0.484
	(0.47)	(0.45)	
Thinks she is Top 20% in Math	0.33	0.24	0.033
	(0.47)	(0.43)	
Confident in Completing College	0.49	0.49	0.904
	(0.50)	(0.50)	
Studying Industrial Engineering	3.05	2.92	0.285
	(1.19)	(1.27)	
Studying Mechanical Engineering	2.72	2.58	0.241
	(1.23)	(1.22)	
Panel C: Perceptions			
Mom Wishes College	0.98	0.96	0.180
	(0.14)	(0.20)	
Dad Wishes College	0.98	0.93	0.036
	(0.16)	(0.26)	
Mom Wishes Engineering	0.14	0.11	0.481
	(0.34)	(0.32)	
Dad Wishes Engineering	0.17	0.17	0.909
	(0.38)	(0.38)	
Teacher Wishes College	0.58	0.72	0.002
	(0.50)	(0.45)	
Teacher Wishes Engineering	0.08	0.10	0.394
	(0.27)	(0.31)	
Gender Attitudes	-0.00	0.08	0.216
	(0.69)	(0.69)	
Self-Efficacy	-0.00	0.02	0.425
	(0.26)	(0.25)	
Panel D: Social Media			
Has IG Account	0.87	0.87	0.940
	(0.34)	(0.33)	
Spends >2hr on social media	0.47	0.48	0.851
	(0.50)	(0.50)	
Followed Account	0.00	0.29	0.000
	(0.00)	(0.45)	
Observations	162	385	

Notes: For each variable, the p-values reported in columns 5 to 7 are generated by tests of equality of means. All variables are measured at baseline. The math and language performance averages in Panel A refer to the final grade obtained at the end of the previous academic year. The highest possible grade is 20. In panel B, confidence in being a top student indicates the percentage of students who answered "yes, definitely" to the respective question. The other confidence questions are average answers on a scale from 1 ("definitely no") and 5 ("definitely yes"). The Gender Attitudes and Self-Efficacy measures are aggregated indexes, which have been standardized around the control mean.

Table 3: Short- and Longer-Term Impacts on Education Preferences and Choices

	Wish Engineering		Scholarship		Enrolled in Engineering		Enrolled in College	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instagram Treatment (T)	-0.070***	-0.070***	0.010	0.016	0.006	0.012	0.162***	0.149***
	(0.021)	(0.021)	(0.032)	(0.030)	(0.018)	(0.014)	(0.061)	(0.048)
	[0.004]	[0.005]	[0.916]	[0.579]	[0.916]	[0.579]	[0.009]	[0.005]
Observations	495	495	547	547	547	547	547	547
Clusters	67	67	73	73	73	73	73	73
Control Mean	0.176	0.176	0.111	0.111	0.068	0.068	0.265	0.265
Randomization Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Value Controls	Yes	Yes	–	–	–	–	–	–
LASSO Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table displays ITT estimates from linear probability models. "Wish engineering" is a 0-1 indicator equal to 1 if the student stated that engineering is her desired field of study in college. "Scholarship" is a 0-1 indicator, equal to 1 if the student applied for the engineering scholarship that we created about 3 months after the intervention. "Enrolled in Engineering" is a 0-1 indicator, equal to 1 if the student is enrolled in college and studying engineering 1 year after graduating high school, and 0 otherwise. "Enrolled in college" is a 0-1 indicator, equal to 1 if the student is enrolled in college 1 year after graduating high school (regardless of major), and 0 otherwise. In all regressions, we control for the randomization strata, which are municipalities, whether the school is co-ed and whether the school is classified as a low SES school. In columns 1 and 2, we include the outcome variable measured at baseline. Controls in even columns are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of baseline covariates displayed in Table 2. Standard errors clustered at the school level are reported in parentheses. Multiple hypothesis corrected p-values using the Romano-Wolf (2005) procedure are reported in square brackets. *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Heterogeneous Impacts by Top Performance in Math

	Wish Engineering		Scholarship		Enrolled in Engineering		Enrolled in College	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instagram Treatment (T)	-0.073***	-0.073***	-0.024	-0.019	0.012	0.018	0.161**	0.139**
	(0.021)	(0.021)	(0.033)	(0.034)	(0.017)	(0.014)	(0.064)	(0.053)
	[0.009]	[0.010]	[0.619]	[0.473]	[0.619]	[0.294]	[0.012]	[0.015]
T x Top	0.030	0.030	0.220**	0.180*	0.011	-0.039	0.049	0.061
	(0.063)	(0.063)	(0.083)	(0.100)	(0.089)	(0.081)	(0.110)	(0.112)
	[0.872]	[0.828]	[0.006]	[0.103]	[0.874]	[0.828]	[0.872]	[0.828]
Top	0.022	0.022	-0.067	-0.130	0.128*	0.065	0.092	-0.036
	(0.054)	(0.054)	(0.041)	(0.084)	(0.069)	(0.069)	(0.081)	(0.099)
Observations	495	495	547	547	547	547	547	547
Clusters	67	67	73	73	73	73	73	73
Control Mean	0.160	0.160	0.121	0.121	0.045	0.045	0.258	0.258
Randomization Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Value Controls	Yes	Yes	–	–	–	–	–	–
LASSO Controls	No	Yes	No	Yes	No	Yes	No	Yes
$H_0 : T + T \times Top = 0$	0.481	0.481	0.026	0.094	0.778	0.786	0.058	0.059

Notes: The table displays ITT estimates from linear probability models. "Wish engineering" is a 0-1 indicator equal to 1 if the student stated that engineering is her desired field of study in college. "Scholarship" is a 0-1 indicator, equal to 1 if the student applied for the engineering scholarship that we created about 3 months after the intervention. "Enrolled in Engineering" is a 0-1 indicator, equal to 1 if the student is enrolled in college and studying engineering 1 year after graduating high school, and 0 otherwise. "Enrolled in college" is a 0-1 indicator, equal to 1 if the student is enrolled in college 1 year after graduating high school (regardless of major), and 0 otherwise. In all regressions, we control for the randomization strata, which are municipalities, whether the school is co-ed and whether the school is classified as a low SES school. In columns 1 and 2, we include the outcome variable measured at baseline. "Top" indicates whether the student was among the top performers (top quantile) in math, based on their final grade on the year preceding the study, i.e, the year before high school graduation. Controls in columns 2 an 4 are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of covariates displayed in Table 2. Standard errors clustered at the school level are reported in parentheses. Multiple hypothesis corrected p-values using the Romano-Wolf (2005) procedure are reported in square brackets. *** p<0.01, ** p<0.05, * p<0.10.

Table 5: Treatment Impacts on Enrollment in Other Fields

	Engineering	Non-Eng STEM	Business & Econ	Medical & Health Sciences	Law	Humanities	Education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instagram Treatment (T)	0.007	0.040***	0.015	0.033	0.023	0.031	0.002
	(0.015)	(0.014)	(0.021)	(0.022)	(0.023)	(0.020)	(0.008)
Observations	547	547	547	547	547	547	547
Clusters	73	73	73	73	73	73	73
Control Mean	0.068	0.025	0.068	0.037	0.031	0.025	0.012
Randomization Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LASSO Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table displays ITT estimates from linear probability models. In all regressions, the dependent variable is a 0-1 indicator equal to 1 if the student is enrolled in college in the corresponding major, and 0 otherwise. In column 2, "Non-Eng STEM" refers to the following non-engineering STEM fields appearing in our data: Math, Statistics, Biology, Architecture and Aerospace Sciences. We control for the randomization strata, which are municipalities, whether the school is co- ed and whether the school is classified as a low SES school. Additional controls are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of covariates. Standard errors clustered at the school level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 6: Shool-level Poisson Regressions

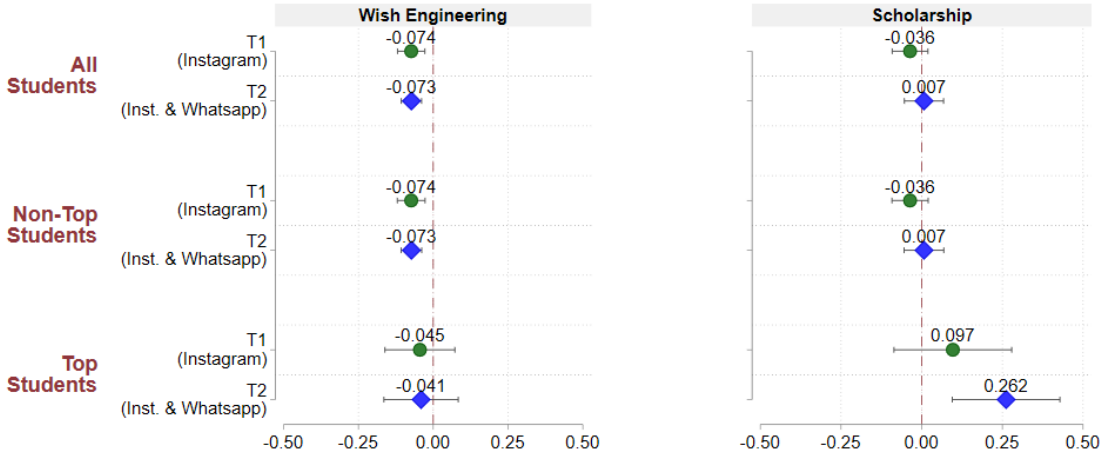
	Wish Engineering		Scholarship		Enrolled in Engineering		Enrolled in College	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instagram Treatment (T)	-0.791***	-0.861***	0.270	0.066	0.325	0.115	0.731***	0.509**
	(0.216)	(0.196)	(0.329)	(0.279)	(0.351)	(0.276)	(0.177)	(0.203)
Observations	73	73	73	73	73	73	73	73
Control Mean	1.040	1.040	0.720	0.720	0.440	0.440	1.720	1.720
Randomization Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Value Controls	Yes	Yes	–	–	–	–	–	–
Exposure Correction	No	Yes	No	Yes	No	Yes	No	Yes

Notes: We report coefficients and 95% confidence intervals School-level Poisson regressions, where the dependent variables are the number of students stating that engineering is their desired field of study in college (columns 1 and 2), the number of students applying for the engineering scholarship that we created (columns 3 and 4), the number of students enrolled in engineering (columns 5 and 6), and the number of students enrolled in college, regardless of major (columns 7 and 8). Odd columns include no exposure correction. Even columns include an exposure correction for the number of girls surveyed at each school. Columns 1 and 2 include baseline value controls, i.e., the number of girls who expressed a preference for the engineering major at baseline. We also control for the randomization strata, which are municipalities, whether the school is co-ed and whether the school is classified as a low SES school. *** p<0.01, ** p<0.05, * p<0.10.

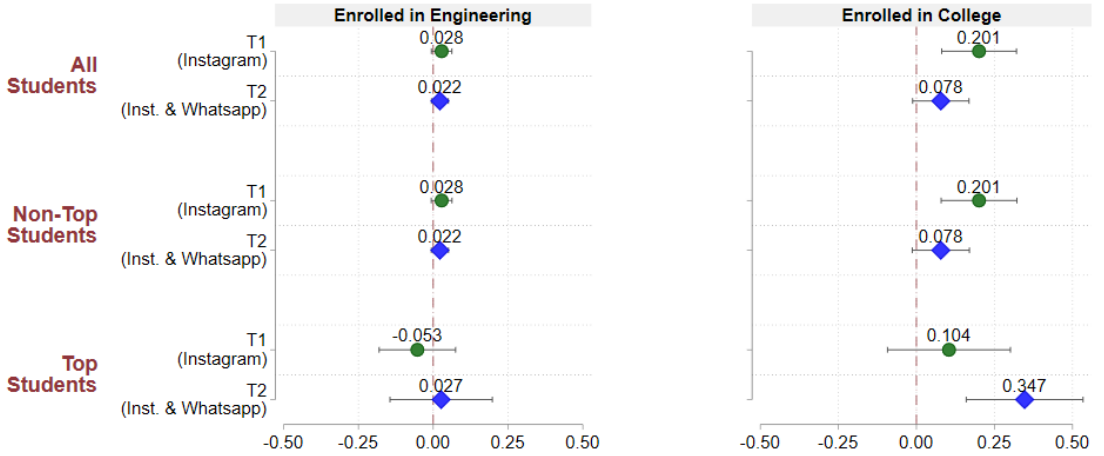
A Appendix Tables and Figures

Figure A1: Treatment Impacts on Education Preferences and Chouces - Separate Treatment Arms

(a) Short-term Outcomes



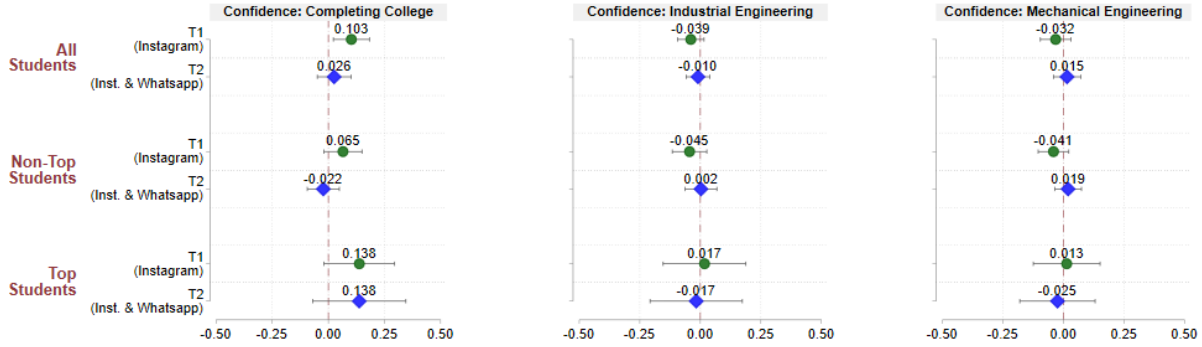
(b) Long-term Outcomes



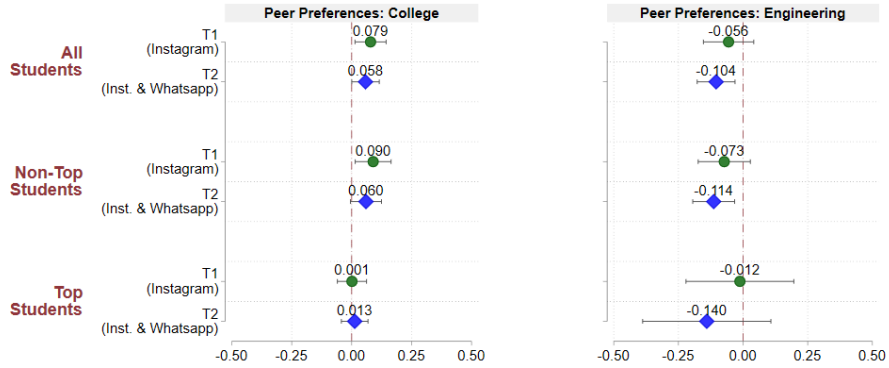
Notes: "Wish engineering" is a 0-1 indicator equal to 1 if the student stated that engineering is her desired field of study in college. "Scholarship" is a 0-1 indicator, equal to 1 if the student applied for the engineering scholarship that we created about 3 months after the intervention. "Enrolled in Engineering" is a 0-1 indicator, equal to 1 if the student is enrolled in college and studying engineering 1 year after graduating high school, and 0 otherwise. "Enrolled in college" is a 0-1 indicator, equal to 1 if the student is enrolled in college 1 year after graduating high school (regardless of major), and 0 otherwise. Controls are selected through the Double Lasso procedure from the full set of baseline covariates, and always include the randomization strata: school-level indicators for low SES status, and co-educational status, in addition to metropolitan area fixed effects.

Figure A2: Mechanisms - Separate Treatment Arms

(a) Confidence



(b)Perception of Peers' Preferences



Notes: In panel (a), The figures report ITT coefficient estimates and 95% confidence intervals linear probability models. In all columns of panel (a), the dependent variables are 0-1 indicators for the student having answers "definitely yes" to an endline question asking if they believed they had the ability to complete college (top left), complete a degree in Industrial Engineering (top middle), complete a degree in Mechanical Engineering (top right). In panel (b), the figures report ITT coefficient estimates and 95% confidence intervals OLS regressions. To measure perceptions of peers' preferences for college and for engineering, we asked students to list and name their three best friends. We then asked if each friend would go to college after graduation, and, if so, what their field of study will be. The outcome variable in column 1 is the number of friends, out of 3, who the student thinks will go to college. The outcome of variable in column 2 is the number of friends, out of 3, whom the student thinks will study engineering. Controls are selected through the Double Lasso procedure from the set of variables displayed in Table 2, and always include the randomization strata: school-level indicators for low SES status, and co-educational status, in addition to metropolitan area fixed effects.

Table A1: Attrition Analysis

	Not Attrited at Endline	
	(1)	(2)
Treatment	-0.012	-0.014
	(0.040)	(0.038)
Low SES School		0.032
		(0.065)
Co-ed School		-0.031
		(0.041)
Parent Went to College		-0.033
		(0.036)
Baseline Interest in College		0.007
		(0.050)
Baseline Interest in Engineering		-0.027
		(0.032)
Top Math Student		0.064**
		(0.025)
Language Score		0.003
		(0.009)
Observations	547	547
Clusters	73	73
Control Mean	0.914	0.914
Controls	No	Yes

Notes: Linear probability models. The dependent variable is a 0-1 indicator, equal to 1 if the student was surveyed both at baseline and endline, and equal to 0 if it she was not re-surveyed at endline. Standard errors, in parentheses, are clustered at the school level. *** p<0.01, ** p<0.05, * p<0.10.

Table A2: Engagement with Instagram Account

	All	T1	T2	H_0 : T1=T2
	(1)	(2)	(3)	(4)
Conditional on Following				
N. Posts Liked	7.47	8.37	6.72	0.267
Liked at least 1 post	0.63	0.67	0.61	0.515
N. Reels liked	2.72	3.10	2.41	0.280
Liked at least 1 reel	0.58	0.63	0.54	0.360
Not Conditional on Following				
Followed Account	0.29	0.27	0.31	0.486
N. Posts Liked	2.18	2.30	2.07	0.676
Liked at least 1 post	0.19	0.18	0.19	0.838
N. Reels liked	0.80	0.85	0.75	0.668
Liked at least 1 reel	0.17	0.17	0.18	0.921
Observations	385	186	199	

Notes: The table reports descriptive statistics on girls' engagement with the Instagram account. The sample is restricted to girls in treatment schools. Girls in control schools were not invited to follow the Instagram account, which was set up as a "private" account. Only girls from treatment schools were therefore granted access.

Table A3: Treatment Take-up (Treatment Group)

	Follow Account		# of Reels Liked		# of Reels and Posts Liked	
	(1)	(2)	(3)	(4)	(5)	(6)
Wants to Go to College	-0.043	-0.009	-1.063	-0.894	-2.885	-2.274
	(0.097)	(0.101)	(0.657)	(0.676)	(2.337)	(2.337)
Interest in Engineering	-0.001	0.008	0.278	0.275	1.061	1.077
	(0.090)	(0.085)	(0.337)	(0.323)	(1.398)	(1.398)
High SES School	0.011	0.012	0.011	-0.003	-0.217	-0.253
	(0.058)	(0.059)	(0.301)	(0.300)	(1.063)	(1.062)
Co-ed School	0.020	0.013	0.058	0.085	-0.075	-0.017
	(0.056)	(0.060)	(0.346)	(0.351)	(1.165)	(1.178)
At Least 1 Parent Attended College	0.006	0.011	0.063	0.130	0.160	0.373
	(0.052)	(0.051)	(0.290)	(0.300)	(0.920)	(0.968)
Has Instagram Account		0.215***		0.553**		2.318***
		(0.065)		(0.259)		(0.852)
Spends >2 Hr on Social Media		-0.008		-0.400**		-1.216*
		(0.036)		(0.194)		(0.663)
Observations	385	385	385	385	385	385
Clusters	48	48	48	48	48	48
Mean	0.29	0.29	0.80	0.80	2.98	2.98
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The analysis is restricted girls in treatment schools. The dependent variable in Column 1 and 2 is an indicator for whether the student followed the account. The dependent variable in Column 3 and 4 is how many reels or posts the student liked, unconditional on whether they followed the account. The dependent variable in Column 5 and 6 is the number of reels or posts liked, only for students who followed the account. "Has IG Account," "Spend >2 Hr on Social media," and "Wants to Go to College" and "Interest in Engineering" are baseline values. All regressions also include municipality fixed effects. Standard errors were clustered at the school-level. *** p<0.01, ** p<0.05, * p<0.10.

Table A4: Balance Table - Boys

	Control	Treatment	C=T
Panel A: Demographics			
Age	16.18	16.15	0.610
	(0.39)	(0.41)	
Mom Went to College	0.38	0.31	0.284
	(0.49)	(0.46)	
Dad Went to College	0.36	0.30	0.331
	(0.48)	(0.46)	
Math Performance	16.84	16.95	0.715
	(1.93)	(2.20)	
Language Performance	16.73	16.71	0.952
	(1.72)	(1.94)	
Top Math Student	0.23	0.19	0.436
	(0.43)	(0.39)	
Wish College	0.95	0.98	0.271
	(0.22)	(0.16)	
Wish Engineering	0.35	0.32	0.628
	(0.48)	(0.47)	
Wish STEM	0.38	0.34	0.619
	(0.49)	(0.48)	
Panel B: Self-Reported Confidence			
Thinks he is in Top 50 % Math	0.45	0.53	0.293
	(0.50)	(0.50)	
Thinks he is in Top 20% Math	0.43	0.39	0.598
	(0.50)	(0.49)	
Confident in Completing College	0.53	0.60	0.321
	(0.50)	(0.49)	
Studying Industrial Engineering	3.62	3.52	0.511
	(1.09)	(1.13)	
Studying Mechanical Engineering	3.43	3.33	0.530
	(1.14)	(1.21)	
Panel C: Perceptions			
Mom Wishes College	0.96	0.96	0.886
	(0.19)	(0.20)	
Dad Wishes College	0.95	0.94	0.917
	(0.22)	(0.23)	
Mom Wishes Engineering	0.27	0.29	0.730
	(0.45)	(0.46)	
Dad Wishes Engineering	0.32	0.33	0.919
	(0.47)	(0.47)	
Teacher Wishes College	0.73	0.68	0.469
	(0.45)	(0.47)	
Teacher Wishes Engineering	0.22	0.27	0.416
	(0.42)	(0.45)	
Gender Attitudes	-0.19	-0.25	0.595
	(0.79)	(0.80)	
Self-Efficacy	0.09	0.12	0.515
	(0.25)	(0.26)	
Panel D: Social Media			
Has IG Account	0.77	0.71	0.328
	(0.43)	(0.46)	
Spends >2hr on social media	0.32	0.33	0.919
	(0.47)	(0.47)	
Followed Account	0.00	0.02	0.167
	(0.00)	(0.16)	
Observations	77	163	

Notes: The table reports the characteristics of the surveyed boys, by treatment assignment. For each variable, the p-values reported in column 3 are generated by tests of equality of means. All variables are generated by the baseline survey students participated in, in July 2023. The math and language performance averages in Panel A refer to the final grade obtained at the end of the previous academic year. The highest possible grade is 20. In panel B, confidence in being a top student indicates the percentage of students who answered "yes, definitely" to the respective question. The other confidence questions are average answers on a scale from 1 ("definitely no") and 5 ("definitely yes"). The Gender Attitudes and Self-Efficacy measures are aggregated indexes, which have been standardized around the control mean.

Table A5: Heterogeneous Impacts by Student Gender

	Wish Engineering	Scholarship	Enrolled in Engineering	Enrolled in College
	(1)	(2)	(3)	(4)
Instagram Treatment (T)	-0.070***	0.022	0.020	0.157***
	(0.021)	(0.033)	(0.020)	(0.053)
T × Boy	0.061	-0.028	-0.014	-0.136
	(0.047)	(0.065)	(0.052)	(0.089)
Boy	0.017	-0.009	0.046	0.121
	(0.042)	(0.059)	(0.042)	(0.074)
Observations	709	787	787	787
Clusters	70	73	73	73
Control Mean	0.176	0.111	0.068	0.265
Randomization Controls	Yes	Yes	Yes	Yes
Baseline Value Controls	Yes	–	–	–
LASSO Controls	Yes	Yes	Yes	Yes
$H_0 : T + T \times Boy = 0$	0.809	0.909	0.885	0.787

Notes: The table displays ITT estimates from linear probability models, where the dependent variables are our four primary outcomes of interest. The sample includes surveyed boys and girls. When available, we include the outcome variable measured at baseline. In all regressions, we control for the randomization strata, which are municipalities, whether the school is co-ed and whether the school is classified as a low SES school. Other controls in are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of baseline covariates. Standard errors clustered at the school level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Impacts on Short- and Long-Term Outcomes. Separate Treatment Arms

	Wish Engineering		Scholarship		Enrolled in Engineering		Enrolled in College	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instagram (T1)	-0.069**	-0.069**	-0.017	-0.011	0.003	0.006	0.203**	0.187**
	(0.027)	(0.027)	(0.035)	(0.033)	(0.025)	(0.018)	(0.084)	(0.071)
	[0.011]	[0.011]	[0.496]	[0.659]	[0.899]	[0.724]	[0.002]	[0.006]
Instagram & WhatsApp (T2)	-0.071***	-0.071***	0.033	0.039	0.009	0.011	0.127**	0.107**
	(0.020)	(0.020)	(0.035)	(0.033)	(0.019)	(0.017)	(0.061)	(0.051)
	[0.005]	[0.005]	[0.240]	[0.157]	[0.651]	[0.525]	[0.043]	[0.049]
Observations	495	495	547	547	547	547	547	547
Clusters	67	67	73	73	73	73	73	73
Control Mean	0.176	0.176	0.111	0.111	0.068	0.068	0.265	0.265
P-value (T1=T2)	0.925	0.925	0.150	0.145	0.308	0.218	0.812	0.795
Randomization Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Value Controls	Yes	Yes	–	–	Yes	Yes	–	–
LASSO Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: ITT estimates from linear probability models, where the dependent variables are 0-1 indicators for the student stating that engineering is their desired field of study in college (columns 1 and 2), for the student applying for the engineering scholarship that we created (columns 3 and 4), for the student being enrolled in engineering (columns 5 and 6), and for the student student being enrolled in college, regardless of major (columns 7 and 8). In all regressions, we control for the randomization strata, which are municipalities, whether the school is co-ed and whether the school is classified as a low SES school. When available, we include the outcome variable measured at baseline. Controls in columns 2 an 4 are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of baseline covariates. Standard errors clustered at the school level are reported in parentheses. Multiple hypothesis corrected p-values using the Romano-Wolf (2005) procedure are reported in square brackets. *** p<0.01, ** p<0.05, * p<0.10.

Table A7: Mechanisms: Impacts of Parents and Teachers' Preferences and Support

	Mom's preferences		Dad's preferences		Teachers' support	
	College	Engineering	College	Engineering	College	Engineering
	(1)	(2)	(3)	(4)	(5)	(6)
Instagram Treatment (T)	0.005	-0.019	0.039**	-0.037	-0.026	0.028
	(0.014)	(0.027)	(0.018)	(0.037)	(0.040)	(0.039)
Observations	495	495	495	495	495	495
Control Mean	0.966	0.135	0.932	0.189	0.676	0.189
Randomization Controls	Yes	Yes	Yes	Yes	Yes	Yes
LASSO Controls	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Value Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table displays ITT estimates generated by OLS regressions. In columns 1 and 2, the dependent variables are 0-1 dummy variables equal to 1 if the student answered "go to college" and "study engineering", respectively, when asked what they thought their mother would want them to after high school graduation. The "Dad's preferences" outcome variables, in columns 3 and 4, are generated by the same questions asked with reference to fathers. The "Teachers' support" outcome variables, in columns 5 and 6, are constructed in a slightly different way. We asked student whether they had discussed going to college with any of their teachers. The outcome variable in column 5 is a 0-1 indicator equal to 1 if the student answered affirmatively. We then asked students what was the field of study that teachers recommended the most. The outcome variable in column 6 is a 0-1 indicator, which is equal to 1 if the student answered "engineering." In all regressions, we control for the randomization strata, which are municipalities, whether the school is co-ed and whether the school is classified as a low SES school. We also include the outcome variable measured at baseline. Additional controls are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of baseline covariates. Standard errors clustered at the school level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A8: Enrollment at the Universidad de Piura

	College		Universidad de Piura	
	(1)	(2)	(3)	(4)
Instagram Treatment (T)	0.162***	0.149***	0.048	0.052
	(0.061)	(0.048)	(0.033)	(0.033)
Observations	547	547	547	547
Clusters	73	73	73	73
Control Mean	0.265	0.265	0.117	0.117
Randomization Controls	Yes	Yes	Yes	Yes
LASSO Controls	No	Yes	No	Yes

Notes: ITT estimates from linear probability models, where the dependent variables are 0-1 indicators for the student being enrolled in college, regardless of major (columns 1 and 2), and for the student being enrolled in the Universidad de Piura (columns 3 and 4). In all regressions, we control for the randomization strata, which are municipalities, whether the school is co-ed and baseline values, where available. Additional controls are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of baseline covariates. Standard errors, in parentheses, are clustered at the school-level. *** p<0.01, ** p<0.05, * p<0.10.

Table A9: Private and Public College Enrollment

	Enrolled in College		Public		Private	
	(1)	(2)	(3)	(4)	(5)	(6)
Instagram Treatment (T)	0.162***	0.149***	0.057**	0.052**	0.105*	0.102*
	(0.061)	(0.048)	(0.027)	(0.025)	(0.058)	(0.053)
	[0.001]	[0.002]	[0.008]	[0.017]	[0.008]	[0.017]
Observations	547	547	547	547	547	547
Clusters	73	73	73	73	73	73
Control Mean	0.265	0.265	0.056	0.056	0.210	0.210
Randomization Controls	Yes	Yes	Yes	Yes	Yes	Yes
LASSO Controls	No	Yes	No	Yes	No	Yes

Notes: ITT estimates from linear probability models. The dependent variables are 0-1 indicators for the student being enrolled in college, regardless of major (columns 1 and 2), and for the for being enrolled in a public university (columns 3 and 4) and for being enrolled in a privae university (columns 5 and 6). In all regressions, we control for the randomization strata, which are municipalities, whether the school is co-ed and baseline values, where available. Additional controls are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of baseline covariates. Standard errors, in parentheses, are clustered at the school-level. Multiple hypothesis corrected p-values using the Romano-Wolf (2005) procedure are reported in square brackets. *** p<0.01, ** p<0.05, * p<0.10.

Table A10: College Enrollment by Institution Quality

	Enrolled in College		High Quality		Lower Quality	
	(1)	(2)	(3)	(4)	(5)	(6)
Instagram Treatment (T)	0.162***	0.149***	0.090*	0.089*	0.072**	0.066***
	(0.061)	(0.048)	(0.051)	(0.046)	(0.029)	(0.024)
	[0.001]	[0.002]	[0.006]	[0.008]	[0.003]	[0.004]
Observations	547	547	547	547	547	547
Clusters	73	73	73	73	73	73
Control Mean	0.265	0.265	0.191	0.191	0.074	0.074
Randomization Controls	Yes	Yes	Yes	Yes	Yes	Yes
LASSO Controls	No	Yes	No	Yes	No	Yes

Notes: ITT estimates from linear probability models. The dependent variables are 0-1 indicators for the student being enrolled in college, regardless of major (columns 1 and 2), and for the for being enrolled in a high quality university (columns 3 and 4) and for being enrolled in a lower-quality private university (columns 5 and 6). In all regressions, we control for the randomization strata, which are municipalities, whether the school is co-ed and baseline values, where available. Additional controls are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of baseline covariates. Standard errors, in parentheses, are clustered at the school-level. Multiple hypothesis corrected p-values using the Romano-Wolf (2005) procedure are reported in square brackets. *** p<0.01, ** p<0.05, * p<0.10.

Table A11: Heterogeneity by Predicted Probability of College Enrollment

	Wish Engineering	Scholarship	Enrolled in Engineering	Enrolled in College
	(1)	(2)	(3)	(4)
Treatment (T)	-0.173***	0.011	0.021	0.273***
	(0.064)	(0.055)	(0.017)	(0.072)
T × Mid Tercile	0.079	0.010	-0.019	-0.091
	(0.058)	(0.060)	(0.043)	(0.080)
T × Top Tercile	0.180**	-0.014	-0.030	-0.238***
	(0.081)	(0.056)	(0.046)	(0.086)
Observations	495	547	547	547
Clusters	67	73	73	73
Control Mean	0.176	0.111	0.068	0.265
Randomization Controls	Yes	Yes	Yes	Yes
T x Mid = T x Top (p-value)	0.218	0.674	0.859	0.176
T + T x Mid = 0 (P-value)	0.075	0.662	0.963	0.049
T + T x Top = 0 (P-value)	0.898	0.924	0.816	0.621

Notes: ITT estimates from linear probability models, where the dependent variables are 0-1 indicators for the student stating that engineering is their desired field of study in college (columns 1 and 2), for the student applying for the engineering scholarship that we created (columns 3 and 4), for the student being enrolled in engineering (columns 5 and 6), and for the student student being enrolled in college, regardless of major (columns 7 and 8). The estimated probability of college enrollment is obtained from an OLS regression estimated using only control-group observations, where college enrollment is regressed on the baseline characteristics reported in Table 1. Students are then divided into terciles of this predicted probability, with the omitted category corresponding to the bottom tercile (lowest predicted probability of college enrollment). In all regressions, we control for the randomization strata, which are municipalities, whether the school is co-ed and whether the school is classified as a low SES school. When available, we include the outcome variable measured at baseline. Controls in even columns are selected using the Double Lasso procedure (Belloni et al., 2014) from the full set of baseline covariates. Standard errors clustered at the school level are reported in parentheses. Multiple hypothesis corrected p-values using the Romano-Wolf (2005) procedure are reported in square brackets. *** p<0.01, ** p<0.05, * p<0.10.