Essays on the Economics of Health and Education

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Dissertation submitted to the Faculty of the
Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
Econometrics and Quantitative Economics

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April 29, 2022
Blacksburg, Virginia

Keywords: STEM gender gap, role models, career choices, academic probation, environmental conditions.

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ABSTRACT

This dissertation brings new causal evidence on three topics in education and health. In the first chapter, I study how in-utero exposure to floods affects the education and health outcomes of individuals. I focus on the 1982-1983 El Niño event in Peru to exploit a natural experiment. I assess the impacts of plausible and exogenous in-utero exposure to excess rainfall on education achievement at adulthood. I find that individuals exposed in-utero to the 1982-1983 El Niño floods, have less chances to have completed primary education at adulthood with different effects by place of residence and gender. In the second chapter, I study how a low-cost face-to-face intervention, that exposed senior-year high school students to female role models affects career preferences and reduces the gender preference gap for STEM programs in Peru in a randomized controlled trial. I find that exposure to role models increased preference for engineering majors only for those girls in the top math ability quartile; and that the effect was stronger for those who reside geographically close to the role models' university. Finally, in the third chapter, I investigate how to optimally allocate students to academic programs. I evaluate external signals of ability transmitted to students by academic probation rules in Peru using a regression discontinuity design. The analysis suggests that academic probation is associated with higher drop-out rates from programs and a deterioration in subsequent academic performance. I conclude that in a society with predominant gender norms, signals of ability could aid to the retention of only qualified students in selected programs with further implications on aggregate productivity and the allocation of talent.

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GENERAL AUDIENCE ABSTRACT

This study sought to understand how exposure to different adverse events in life affects individuals' decision choices. I focus on a developing country, Peru, where returns to education are high and investment in human capital can improve individuals' lives. In the first chapter, I study how prenatal exposure to extreme weather conditions (i.e. the 1982-1983 El Niño floods in Peru) affected the education achievement of those individuals when they were older. This adverse and unpredictable event, affecting the evolution of babies while in-utero, during the nine months of gestation, reduced the probability that the exposed individual had completed primary education. In the second chapter, I implement an experiment in the field to understand the effect of the exposure to role models on the reduction of the gender gap in careers that are male dominated such as Science, Technology, Engineering, and Mathematics (STEM). The gender gap in STEM fields is a major cause of concern for policymakers around the world since it not only contributes to talent misallocation but also critically deepens gender-based socioeconomic inequalities. I find that a brief exposure to role models of about 20 minutes increases preferences for engineering majors of high talented female high school students, and I attribute this to inspiration rather than information mechanisms. The evidence suggests that, inspired by role models, high math ability girls had increased self-confidence for succeeding in engineering majors. Finally, in the third chapter I investigate the misallocation of students to academic programs and more specifically the effect of one university policy related to academic probation on attrition rates and subsequent academic performance. Academic probation is a warning received by students failing to make substantial academic progress required for graduation. By receiving academic probation, students get additional information of their capabilities to successfully complete a degree. The analysis suggests that academic probation is associated with higher drop-out rates from programs and a deterioration in subsequent academic performance aiding to the retention of only qualified students in selected fields of study.

This dissertation is dedicated to my family. For their endless love, support, and encouragement in this long journey to knowledge.

Acknowledgments

I am indebted to my advisor, Sudipta Sarangi, and my dissertation committee members for their guidance and advice throughout my doctoral studies. This dissertation would have not been possible without their support. My advisor and some committee members aided in the writing and research behind one of my chapters presented as part of this dissertation. A brief description of their contributions is included here:

Chapter 2: To inspire and to inform: The role of role models.

Marcos Agurto, Ph.D., is currently a professor in the Department of Economics at Universidad de Piura. Dr. Agurto served as a co-author on this paper and helped in the implementation of the experiment in Peru, the analysis of the data and the writing of the paper.

Sudipta Sarangi, Ph.D., is currently a professor in the Department of Economics at Virginia Tech. Dr. Sarangi served as a co-author on this paper and helped in the revision of previous versions, grant applications for funding the project, and the writing of the paper.

Siddharth Hari, Ph.D., is currently an Economist at the World Bank. Dr. Hari served as a co-author on this paper. His main contributions included the implementation of the field experiment, survey design, and data collection.

Also, I would like to thank my parents for their patience and understanding when undertaking my research and writing my dissertation. Finally, I would like to thank God, his wish was for me to successfully complete this chapter of my life. I will keep on trusting you for my future.

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1

Introduction

This dissertation explores three topics on education and health.

In the first chapter I study how floods may prevent the accumulation of human capital and education completion, and it can also increase the probability to suffer chronic diseases. Particularly, in developing countries, individuals are struggling to protect themselves against climate change and that could have adverse effects on individuals' long-term outcomes in health and education. In this chapter I bring new evidence by exploiting both the geographic and timing variation in exposure to the 1982-1983 El Niño floods to study how in-utero and early in life exposure to extreme weather conditions like floods affect the probability of completing primary education, secondary education, and suffer chronic diseases later in life.

The identification strategy of the causal effect of rainfall variation on education completion and health outcomes relies on the assumption that, conditional on several cohort of birth and district of birth fixed effects, temporary rainfall deviations from the historical averages are uncorrelated with other latent determinants of education completion and health outcomes during gestation and through adulthood. I document decreases in the proportion of individuals that reported to have completed primary education in urban zones if those individuals were exposed in-utero to the shock. In addition, I also find that exposed individuals in rural zones were positively affected by the 1982-

1983 El Niño, reflected by the increase in the probability to have completed secondary education at adulthood, and total years of education. While I find these effects using plausible exogenous exposure to the 1982-1983 El Niño event, most of the negative effects on education outcomes become insignificant using a more recent and predictable El Niño event of 1997-1998. Moreover, I show that early in life exposure to the event, after birth and up to two years of age, does not have significant impacts on individuals' outcomes. To do the analysis, I use the Peruvian National Household Survey (ENAHO) over the period of 2001-2017 to construct an indicator of education completion, and I combine it with rainfall data from the University of Delaware's Terrestrial Precipitation project. This research contributes to the literature on environmental shocks and climate change and a growing body of research on rainfall shocks in developing countries.

In the second chapter, I bring new evidence on how randomized exposure to role models affects the gender gap in STEM. To do this, in collaboration with a group of researchers, I implement and evaluate a randomized role model intervention at the school level, in which female engineering college seniors and very recent female engineering graduates gave talks of approximately 20 minutes to high school students. I find that exposure to a female engineer role model increases female high school students' preferences towards male dominated majors. The effects are of considerable size and concentrated among high math ability girls in schools located geographically close to the role models' place of residence and university: The face-to-face interaction with a female role model is associated with a 14.1 percentage points increase in the decision to plan to enroll in any type of engineering for this sub-sample of students. Even though I find strong effects for girls, I also find weak evidence suggesting that low math ability boys increase their preferences for engineering majors by 6 to 7 percentage points.
Recent studies beyond the laboratory setting show that in-person exposure to female role models may affect the perceptions and gender stereotypes in society. This study contributes to a literature on the impacts of exposure to female role models as well as a body of research on the determinants of the lack of women in STEM.

Finally, in the third research chapter, I examine the mismatch of students to academic programs at Higher Education using a regression discontinuity design and signals of ability through out academic probationary rules in college. Few studies show that academic probationary rules may serve as a wake-up call to some students and determine college attrition rates and performance. I assemble a unique dataset with information on the characteristics and college outcomes of every student in engineering and management programs at a university in Peru, including grade point average for each academic period, students' drop-out rates at the end of each academic term, graduation rates, and baseline characteristics of students. Comparisons across students in a close distance to the probationary cutoff show that students under academic probationary status are more likely to quit their program and to perform badly in subsequent periods but the impacts are different by gender and field of study. The effects on drop-out rates are positive and significant for men in STEM fields whereas the effects on academic performance are negative and significant for women in non-STEM disciplines. In a society with predominant gender stereotypes, and where men are encouraged to enroll in male dominated majors by family and friends, university policies like academic probationary rules may mitigate the student-academic program mismatch with further implications in the allocation of talent and aggregate productivity. These findings motivate a closer discussion of possible mechanisms of student-university program mismatches as well as university policies to retain skilled students in STEM and non-STEM majors.

2

The Impact of In-Utero Flood Shocks on Education Achievement: Evidence From El Niño in Peru

2.1 Introduction

As individuals are exposed to weather shocks they are subject to risks and negative consequences on individuals' well-being. In addition to contemporaneous effects, the effects of certain types of shocks may still be present many years or even decades later. Previous studies have examined the effect of early-life exposure to extreme weather conditions on individuals' long-term educational and health outcomes. However, there are no studies that intend to compare shocks in terms of predictability. Certain types of weather phenomena may be predictable or recurrent and to the best of my knowledge, no studies have examined the predictability of the shocks and how this can impact individuals' outcomes differently. If the shock is anticipated then it could be possible to prepare for it and to take further mitigating steps. Moreover, this study evaluates the long-term effects of floods brought by "El Niño" phenomenon in a developing country like Peru, a territory affected by the event and where the direction of the effect (i.e. positive or negative) is not clear.

In the particular context of "El Niño"[1], which is a climate pattern that describes the unusual warming of surface waters in the eastern tropical Pacific Ocean, its impact on education and health outcomes has been examined before. However, there are no studies that compare "El Niño" shocks that happen in different periods of time and how predictability of the shocks affects individuals' outcomes. This paper contributes to the literature as it investigates the persistent effects of an in-utero exposure to severe floods during the 1982-1983 El Niño event in Peru on human capital formation, and it contrasts the effects of the 1982-1983 El Niño event with the effects of similar El Niño shocks that happened in Peru with different anticipation and intensity. I exploit two sources of variation: i) cohort variation, ii) geographic variation in the exposure to severe floods that occurred in Peru during 1982-1983. This setting introduces an exogenous exposure to a negative environment while in-utero to measure its causal effects on long-term outcomes.

In recent decades, scientists have come to appreciate how significantly El Niño Southern Oscillation (ENSO) impacts can vary from event to event and this variation across events makes it difficult to understand how climate change will influence future ENSO events. According to NOAA, "Extreme El Niño and La Niña events may increase in frequency from about one every 20 years to one every 10 years by the end of the 21st century under aggressive greenhouse gas emission scenarios, and the strongest events may also become even stronger than they are today."[2] Given the increase in the frequency of occurrence of El Niño due to climate change, the development of tools to forecast El Niño can help mitigate its adverse effects.

The effects of in-utero exposure to events on short-term and long-term outcomes have been documented in several studies.[3] Most of these studies support the "fetal origins" hypothesis. According to the "fetal origins" hypothesis, and its proponent, David Barker, the nine months in utero is one of the most critical periods in a person's life because cognitive abilities and health paths at adulthood strongly depend on the intrauterine environment [[13], [6]]. Adverse shocks that affect a

[1] El Niño means "The Little Boy" and it refers to the period of the warming of the sea's surface temperature during the summer months in the southern hemisphere. Source: https://oceanservice.noaa.gov/facts/ninonina.html.

[2] For details please see: https://research.noaa.gov/article/ArtMID/587/ArticleID/2685/New-research-volume-explores-future-of-ENSO-under-influence-of-climate-change

[3] See for instance [5], [24], [55], [6], [7], [74] [116].

fetus' health may lead to worse health in the future, worse education outcomes such as less cognitive achievement, education attainment, human capital accumulation, and lower productivity.[4] For instance, [4] study the negative effects of in-utero exposure to the 1959-1961 China Famine on human capital formation. [5] collects data from the 1918 Influenza Pandemic in the U.S. and analyzes outcomes later in life. In Almond's study cohorts affected by the pandemic while in-utero had on average less education, lower earnings, and more physical disabilities than adjacent cohorts unaffected by the pandemic. [118] find a significant adverse effect of exposure during the first trimester of gestation to the 1944-1945 Dutch Hunger Winter on employment outcomes using administrative data from the Dutch population. Similarly, [12] use regional variation in the timing of exposure to the phylloxera event (1863-1890) to explore long-term impacts on health, life expectation, and adult height. More recently, [106] study the impacts of in-utero exposure to Hurricane Catarina on infant health outcomes, birth weight, and post-neonatal mortality. Even if all the studies mentioned above show that shocks experienced while in-utero affect individuals' outcomes, these studies have not investigated heterogeneous effects by the predictability of the shocks.

Another branch of literature explores the relationship between changes in weather conditions (i.e. temperature, precipitation) that affect the development of humans while in-utero and their long-term outcomes.[5] For example, [91] assess the impact of rainfall shocks observed in-utero and during the first two years of life using longitudinal data from rural China. The results show that shocks in-utero and during the first year of life are important and have negative consequences on cognitive skills without any impact on the formation of non-cognitive skills.[6] [97] investigate the effect of early life shocks, in particular weather shocks on the well-being of individuals, adult health, education attainment, and socio-economic outcomes. The authors found no effect of exposure to extreme rainfall prior to the date of birth, but they found that exposure to shocks during the early infancy (first year of life) has the most important influence on future outcomes for women but not for

[4] A growing body of literature supports the negative short-run and long-run impact of shocks experienced early in life or in-utero. See for instance [64], [85], [107], [109], [115], [125], [127], [124], [89], [26], [81], [47], [42], [40], [39], [37].

[5] See for instance [2], [8], [28], [70], [110], [114].

[6] A more recent study, [86] find evidence that in-utero exposure to drought is associated with lower weight-for-age z scores and the probability of malnutrition in rural India. [43] using longitudinal data from Young Lives in India find negative effects of in-utero exposure to rainfall shocks on cognitive and non-cognitive skills.

men. Women exposed to weather shocks during childhood attain greater height, were more likely to complete grades of schooling, and they live in wealthy households measured by the asset index. In contrast, men were not affected by early life shocks. The authors suggest that rainfall exposure determines nutrition in infancy variation through intermediate channels such as crop production, household income, and food availability. Another study, [119], finds that positive rainfall shocks increase the opportunity cost of child labor, and lead to a switch out of school into productive work. Overall, the effects of exposure to extreme weather conditions on education and health outcomes vary across events and depend on the context.

Among the studies looking specifically at “El Niño”, [1] investigate the exogenous exposure to weather variations due to the 1997-1998 “El Niño Southern Oscillation (ENSO)” during early childhood on children’s physical condition, children’s behavior, and cognitive skills in Mexico. On average, children who were affected by the shock have lower weight and height, and a decrease in cognitive skills (i.e. language development, working memory, visual-spatial thinking) compared to their peers who were not exposed to the shocks. The authors attributed the effects to a decline in household income and a substitution of food intake. Another recent study that uses data from Ecuador and exposure to the 1997-1998 “El Niño” is [116], which finds that the event had negative and significant impacts on individuals’ middle-term outcomes like vocabulary test scores and height. My study adds to the previous literature by contrasting different El Niño events (1982-1983 and 1997-1998) and exploring the effect of in-utero and early in life exposure to these events on individuals’ long-term outcomes in Peru, a territory with predominant socio-economic inequalities and where almost 33% of individuals have income from agricultural activities.[7]

Climate change has affected regions located along the coasts of northern Peru and Ecuador by increasing the frequency of extreme El Niño events, leading to intensifying floods. There have been three extreme “El Niños”- 1982, 1997, and 2015, when temperatures have surpassed historical records and intense rainfall shocks were observed. During “El Niños” of 1982 and 1997, the Peruvian territory was affected by intense floods and high temperatures along the coast. The events

[7] The majority of workers in the agricultural sector are from rural areas (84%). The 1981 Population Census revealed that 65.2% of the individuals lived in urban areas and that the poverty rate was 30%. See for instance, [77].

lead to a deterioration of the infrastructure, disruption of access to public services, negative effects on agriculture, and industrial production [14].[8] Despite the similarities between 1982 and 1997 "El Niño", [59], [68], and [67] have shown that the 1982 "El Niño" was less predictable than the 1997 "El Niño" and it brought higher deaths and economic losses.[9]

I examine the impact of in-utero exposure to a less predictable and more intense the 1982-1983 "El Niño" on educational achievement 17 years later. In Peru, returns to education are high, and individuals with more years of education earn more on average. The return to tertiary education is approximately three times the return to secondary education, which is a clear sign of a severe problem in income distribution.[10] In addition, even though the proportion of individuals between 12-13 years old who have completed primary education has increased by 21% between 2001 and 2015, still the average years of education in Peru is ten years [62], which is equivalent to 10th Grade in the US, and less than high school completion.[11] Among the reasons why individuals do not complete school is the lack of cognitive skills and non-cognitive skills.

I combine the rainfall data from the University of Delaware's Terrestrial Precipitation project with Peruvian household survey datasets.[12] I exploit the timing of birth variation and the geographic variation in exposure to floods to identify causal effects on education outcomes. I restrict the sample to individuals born between 1975 and 1983 to alleviate the concern of time-varying unobservable confounders. In the empirical design, I compare the probability of completing primary (secondary) education for individuals exposed and not exposed to floods during the 1982-1983 El Niño event in a district (municipality). The availability of data also permits the analysis of different specifications controlling for socio-demographic characteristics, survey year, cohort of birth, and district

[8] See: https://www.focus-economics.com/blog/posts/peru-el-nino-still-on-economic-radar, https://blogs.worldbank.org/transport/what-el-ni-o-has-taught-us-about-infrastructure-resilience.

[9] See for instance [35], [113].

[10] The job opportunities of university graduates vary based on the region of residence of the graduates, the characteristics of the universities/colleges they graduated from, the economic sectors in which they work and the career they studied. College graduates, who are 21-35 years old and compared with young people of the same age group with technical studies only or without higher education completion, face low unemployment rates, low informal employment, and they receive better remuneration. College graduates are 31.4% less likely to be underemployed, 58.3% more likely to find a formal job, and earn 73.7% more than their peers without higher education. Source: [123], https://cdn.www.gob.pe/uploads/document/file/1230044/Informe%20Bienal.pdf

[11] The calculations use the sample of individuals who are 25 years or older.

[12] The datasets used in this study are public available and can be downloaded from the Peruvian National Institute of Statistics (INEI) website. The main dataset is the Peruvian National Household Survey (ENAHO).

fixed effects in the regressions. The results show that individuals who are 16 years old or older at the time of the survey, and who were exposed in-utero to the floods during the 1982-1983 El Niño event are less likely to have completed primary education by 1.5 percentage points (significant at the 5%), exclusively for those individuals living in urban areas. To test the validity of my identification strategy, I control for several fixed effects and I perform falsification tests to rule out the presence of confounding factors.[13] On the other hand, my results suggest that in-utero exposure to the more predictable El Niño event of 1997-1998 did not affect education outcomes later in life. One possible explanation is that people can prepare for anticipated shocks and thus mitigate their impacts. Overall, this study highlights the importance to increase the predictability of events such as El Niño, which might be happening more frequently due to climate change. National authorities should devote efforts to the development of sophisticated methods to improve weather forecasts.

2.2 Empirical Setting

2.2.1 El Niño Phenomenon

Understanding the long-term effects of weather shocks on human capital accumulation, and the mechanisms that drive them is key in the context of climate change. My study evaluates the effect of El Niño shocks on primary education completion as the main outcome in Peru. During an El Niño event, the surface waters in the Pacific Ocean become significantly warmer than usual. That change is tied to the atmosphere and to the winds blowing over the Pacific. Easterly trade winds blowing from the Americas to Asia falter and turn around westerlies (in the opposite direction). Because of that, a great quantity of warm water comes to the Americas. Moreover, it produces reversing ocean currents along the equator and along the west coast of South and Central America. El Niño events occur roughly every two to seven years and it alternates with its sibling La Niña. La Niña is a cooling pattern in the eastern Pacific. In order to determine when we have El Niño, sea surface temperatures are measured from time to time from space by satellite radiometers, which

[13] Through a balance test, I show that socio-demographic characteristics of family members and individual characteristics do not drive the results.

can detect the electromagnetic energy, light and heat emitted by objects and surfaces on Earth. The National Oceanic and Atmospheric Administration (NOAA) records of the sea temperature are used by the climatologists at NOAA to examine the occurrence of El Niño. An El Niño is declared when the average temperature in the east-central tropical Pacific stays more than 0.5 degrees Celsius above the long-term average for five consecutive months. In addition, the Southern Oscillation Index can be used to detect El Niño events by observing the atmospheric pressure pattern. According to this index, which computes the difference of monthly pressure release between Tahiti (French Polynesia) and Darwin (Australia), El Niño event happens when the actual Southern Oscillation Index value differs greatly from its average historical value. El Niño has both positive and negative consequences. Among the negative impacts of El Niño, the Peruvian Ministry of Environment mentions the loss of agricultural land, destruction of infrastructure (i.e. machines, bridges, roads, schools, hospitals), telecommunication networks, deaths or migration of flora and fauna (animals and plants), and the increase of diseases such as the Cholera and Malaria [100].[14] On the other hand, El Niño also has positive effects such as better conditions for rice cultivation on the Coast, regeneration of dry forest due to high intake of rainfall, an increase of green areas, the appearance of temporary grasslands in the Northern Coast of Peru which benefits farming, and it also regulates low-temperatures in the highlands by increasing them [45].

The 1982-1983 El Niño was very intense and it produced losses of approximately one billion dollars (USD).[15] In Northern Peru, it rained from December 1982 to June 1983. As a consequence, the volume of water in the main rivers of the Coast increased leading to floods and the formation of numerous streams. The climate change due to the 1982-1983 El Niño also produced droughts in the south and in the Peruvian highlands, affecting severely all socio-economic activities in Peru. The affected population was 6 million, which represents about a third of the national population in 1983. The economic impact of this disaster was reflected in the significant decrease in the country's

[14] Near 2600 kilometers of roads were destroyed during the flood disaster of 1982-1983. Also, 47 bridges collapsed, this affected public and private transportation of people as well as the transportation of food for internal consumption. 8500 people died in accidents or for diseases and 260 health centers had difficulties in daily operations or service provision. See: http://www.indeci.gob.pe/compend_estad/1997/6.2_fenom.pdf.

[15] Source: INDECI, Compendio Estadístico: https://portal.indeci.gob.pe/wp-content/uploads/2019/01/6.2_fenom.pdf.

Gross Domestic Product, which decreased by 12%. In addition, 15 regions were affected: Tumbes, Piura, Lambayeque, La Libertad, Lima, Cajamarca, Junin, Ayacucho, Huancavelica, Apurimac, Cusco, Arequipa, Puno, Moquegua, and Tacna.

The 1997-1998 El Niño episode (November 1997- May 1998) marked the first time that Peruvian scientists predicted the severe El Niño episode six months before heavy rains began [14], [68]. The Peruvian government implemented a prevention plan that centered on the preservation of infrastructure (i.e. schools, churches, hospitals) by the provision of proper drainage for the excess rainwater [68]. The Peruvian National Meteorology and Hydrology Office (SENHAMI) detected an increase in the sea temperature on the Coast in 1996, and these levels turned out to be sufficiently high enough by May 1997, the moment that a contingency plan was implemented by the Peruvian government.

At the end of November 1997, an extreme El Niño took place. The National Institute of Civil Defense reported that the first damages occurred on the 6th of December in Tumbes and Piura region, in Northern Peru; after that El Niño continued to spread to the other regions of the country. The highest impact of the 1997-1998 El Niño was in the agricultural sector. For example, high temperatures affected crop production and led to the appearance of insect pests. In addition, the mortality rates of the animals rose, which are the main resource in the diet of families in rural areas.[16] The high intake of rainfall between November 1997 and April 1998 affected households. Houses near the rivers were destroyed by the floods. In rural areas, many houses made with precarious materials (i.e adobe and concrete) collapsed. The houses in the southern areas, although were not affected by torrential rains, suffered extensive damage due to avalanches of mud. Because of its predictability, the 1997-1998 El Niño's effect on individuals' outcomes might be mitigated and very different from the 1982-1983 El Niño. The Development Bank of Latin America (CAF) and CEPAL have estimated that the total losses of the 1997-1998 El Niño are USD 3.5 billion and the regions more affected were Piura, La Libertad, Lambayeque, Tumbes, Ica, and Loreto.[17]

[16] During the 1997-1998 El Niño, the health system collapsed because of the proliferation of acute diseases such as diarrhea and respiratory infections.

[17] The total losses of the 1997-1998 El Niño in 1983 dollars are USD 2.1 billion.

2.2.2 The Education System in Peru

In Peru, education is compulsory from the age of 5 to the age of 16, with the school year running from March to December, as Peru is located in the Southern Hemisphere. The school system consists of six years of primary education and five years of secondary education. According to [78], the matriculation rates in primary school are high, and in both rural and urban areas almost all boys and girls aged 6 to 11 years old are enrolled in primary education (92.1% in 2017 versus 93.9% in 2007), with no observed differences by gender in school attainment.[18] Despite high attendance rates, the level of education achieved by individuals is very low.[19] For instance, in Peru the average years of education for a person who is 25 years old or older are 10 years (equivalent to Grade 10 in the U.S.). The average years of education in rural and urban zones are 6.9 and 10.6, respectively, with a gap of 3.7. Moreover, gender differences in years of education completed are notable in the Peruvian context. While a woman of 25 years old or older has studied on average 9.7 years, a man of the same age has completed 10.2 years of education. Another determinant of education completion in Peru is race. Individuals who have Spanish as a mother tongue have 2.9 more years of education than individuals whose native language is not Spanish. Socio-economic inequality and poverty prevent individuals to complete more years of education. Individuals in the top 20 percentile of the income distribution study 12.4 years on average. In contrast, individuals in the bottom 20 percentile have on average only 6.8 years of education. The maximum level of education completed varies by location and gender. People of 25 years or older in urban areas have a higher level of education than similar people in age but living in rural zones. For instance, more than half of rural residents have at most completed primary education (52.1%). 27.9% of people in rural areas have completed secondary education and 13.1% have at most some years in kindergarten. On the other hand, a higher proportion of individuals living in urban areas report having completed secondary education (41.2%). Individuals in urban areas are also more likely to enroll in Higher

[18] In 2017, 92 out of 100 boys; and 91 out of 100 girls attended primary education.

[19] Despite advances in education enrollment and school attendance, in Peru still exists a great portion of individuals who have not completed enough years of education. In 2017, 5.2% of people who are 25 years old or older have not attended primary school (only kindergarten), 26% have attended primary school only but not secondary school, 38.6% have completed primary and attended high school but not enrolled in Higher Education. Finally, 30.1% of individuals aged 25 or older have pursued studies at university or technical studies.

Education than people in rural zones.[20] There are gender disparities in total years of education: more men have achieved secondary and Higher Education. According to the descriptive statistics from the Peruvian National Household Survey, 23.7% of men and 28.3% of women have primary education as the maximum level of education achieved. 42.9% of men and 34.4% of women have at most secondary education. 17.9% of men and 14.5% of women pursue college studies.

2.3 Data

The main data for this study comes from the Center for Climatic Research, University of Delaware (UDel).[21] and the Peruvian National Household Survey (ENAHO) administered annually by the Peruvian National Institute of Statistics (INEI). I combine these two datasets to assess the effect of different El Niño events on educational outcomes.

The 1982-1983 El Niño had a huge impact on the North Coast of Peru with activity peaks between December 1982 to June 1983. I use the geographic and timing exposure to the 1982-1983 El Niño to assess the effect of in-utero exposure to weather shocks on the probability of school completion. In order to identify the exposure to floods in-utero, I match latitude and longitude coordinates of the individual's place of birth to the nearest point for which I have rainfall data.[22]

Using monthly precipitation data, I measure excess rainfall for each month during the shock (m) and closest Peruvian district[23] point (d) as the deviation of the observed precipitation in that month from the long-term mean (1970-2001) divided by the historical monthly standard deviation following [116].[24]

$$excess\_rainfall_{myd} = \frac{P_{myd} - \bar{P}_{md}}{\sigma_{md}} \tag{2.1}$$

[20] In urban and rural zones, 16.2% and 4.4% of individuals mention accomplishing Higher Education studies at a non-college/university institution. Similarly, 19.6% of people in urban zones and 2.5% of individuals in rural areas have enrolled in college or university.

[21] UDel's dataset provides geo-referenced information on global monthly terrestrial precipitation (in mm) over the period 1900-2017 for each node at a spatial resolution of 0.5 × 0.5 degrees.

[22] Precise coordinates of the district where the individual was born are not available, however, I use coordinates of the center of each of the districts where the individual was born.

[23] The Peruvian territory is divided into three administrative units: i) regions, ii) provinces, and districts (municipalities). Regions and districts are the largest and smallest administrative units in Peru, respectively. There are in total 1874 districts across the Peruvian territory.

[24] There is no consensus in the literature on how long the historical rainfall series should be to identify extreme monthly rainfall.

Where P_{myd} is the precipitation for a given month (m) in the year (y) at the closest grid point from the center of the district where the individual was born (d). $\bar{P}_{md}$ is the long-term mean (1970-2001) for month (m) at location (d), and σ_{md} is the historical standard deviation.

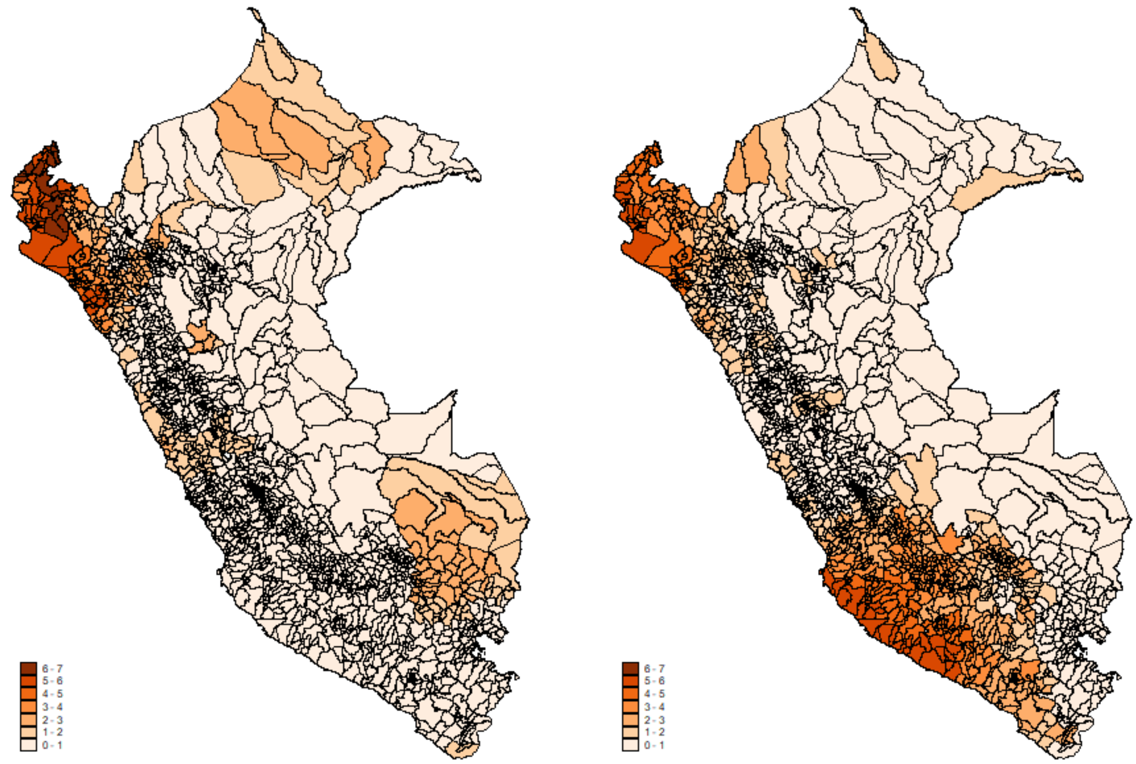
At the district of birth, I calculate exposure to the 1982-1983 El Niño as the number of months (between December 1982 and June 1983) when the excess of rainfall was equal to or greater than one historical standard deviation.

$$nino\_shock_d = \sum_{m=dec82}^{Jun83} \mathbb{1}[excess\_rainfall_{dm} \geq 1] \tag{2.2}$$

Figure 2.1 shows the intensity of the 1982-1983 El Niño and the 1997-1998 El Niño by district in Peru. Notice that the intensity of the floods during this time is heterogeneous among districts. For instance, districts more affected by the 1982-1983 shock are located in the north coastal region, while those located in the jungle and the south were less affected. Figure 2.2 depicts the precipitation in millimeters (mm) observed during the period 1970-2017 for the whole country and for Piura (one region more affected by El Niño shock); while Figure 2.3 describes the evolution of precipitation for Lambayeque and Tumbes, other regions heavily impacted by the shock.

In order to measure the effect of in-utero and early-life exposure to severe floods on educational outcomes, I use data from repeated annual cross-sections of the Peruvian National Household Survey (ENAHO) administered annually by the Peruvian National Institute of Statistics (INEI). The survey uses a probabilistic sample procedure and it is representative at the national and regional levels when using the annual cross-section. Educational outcomes are recorded in the module-specific to Education. ENAHO provides information on all the household members and their last level of education achieved.[25] An advantage of using ENAHO is that it provides information on

[25] I construct three indicators of education: primary education completion, secondary education completion, and total years



(a) Number of months of intense floods during the 1982-1983 El Niño

(b) Number of months of intense floods during the 1997-1998 El Niño

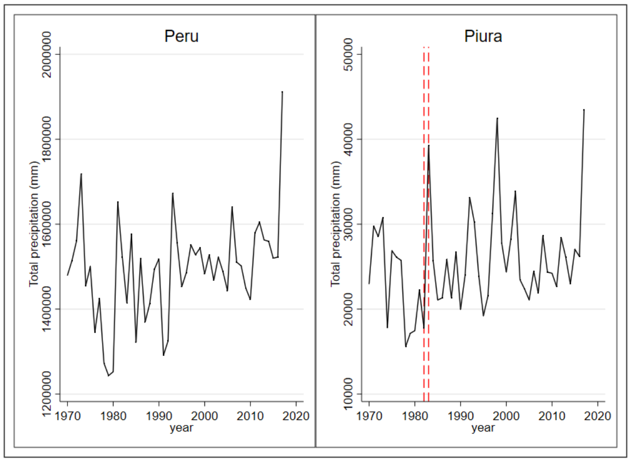
Figure 2.1: Prevalence of excess rainfall by Peruvian district

the individual's place of birth, the individual's place of residence at the time of the survey, and the individual's date of birth. Contrary to previous studies that use place of residence as a proxy for place of birth, I can control for place of birth time invariant characteristics that could potentially affect individuals' development and school achievement. Also, this information allows to explore location of birth and time of birth variations in exposure to El Niño floods while in-utero. The date of conception and the gestation period of each individual is defined using information about the date of birth and assuming 9 months as an approximation of a normal-term pregnancy. For my analysis, I use the annual surveys from 2001 to 2017.[26]

of education. Primary education completion is a dummy variable which equals to one whenever the individual's highest level of education is at least primary school completion, and zero otherwise. A similar approach is used to construct the secondary education completion indicator.

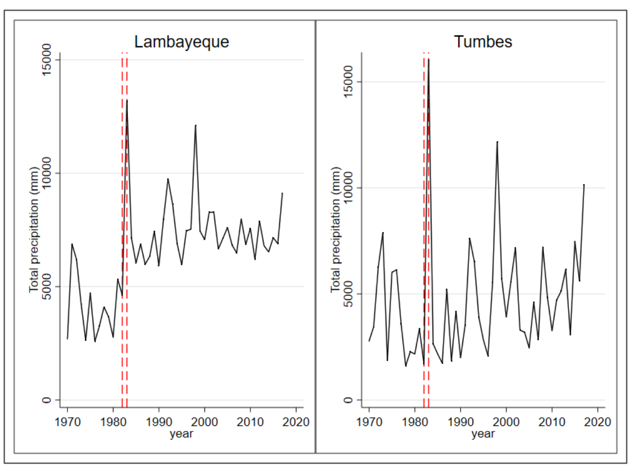
[26] In a complementary study that uses the Peruvian Demographic Health Survey (DHS), I investigate potential mechanisms of individuals' low-education achievement following an in-utero exposure to El Niño floods. I find that children born around the time of the 1997-1998 El Niño, a shock more predictable compared to the 1982-1983 El Niño, had lower weight at birth.

Figure 2.2: Historical Records of Precipitation (mm): 1970-2017



Notes: This figure shows annual historical records of precipitation in mm for the period 1970-2017. The red vertical dashed line is the total annual precipitation in mm observed during the 1982-1983 El Niño. Source: Data from the University of Delaware's Terrestrial Precipitation project: http://climate.geog.udel.edu/~climate/html_pages/download.html#P2017.

Figure 2.3: Historical Records of Precipitation (mm): 1970-2017



Notes: This figure shows annual historical records of precipitation in mm for the period 1970-2017. The red vertical dashed line is the total annual precipitation in mm observed during the 1982-1983 El Niño. Source: Data from the University of Delaware's Terrestrial Precipitation project: http://climate.geog.udel.edu/~climate/html_pages/download.html#P2017.

Because of the absence of historical records around the 1980s in the DHS, I cannot perform a similar approach for the 1982-1983 El Niño. Nevertheless, given its less predictability, I expect stronger effects of in-utero exposure to the 1982-1983 El Niño on health outcomes.

In order to examine the effect of the 1982-1983 El Niño on education completion rates, I constraint the data to individuals (daughters or sons of the head of the household),[27] who were born during the period 1975-1983, this allows me to compare cohorts of individuals born very close and experienced similar changes in macroeconomic conditions. I can also compare across siblings with this restriction. In this sample, some individuals will be exposed to the 1982-1983 El Niño while in-utero or during early life (0-2 years old); while other subjects will not be exposed to the event. The sample comprises information from 36 057 individuals in 1301 districts.

I also explore the effect of in-utero exposure to a more predictable El Niño on education completion (the 1997-1998 El Niño). For this purpose, I constraint the sample to individuals (daughters or sons of the head of the household), who were born during the period 1990-1998. The sample comprises information from 58 391 individuals in 1424 districts.

A possible concern is that because the total districts of birth included in the subsamples are different, any difference in the consequences of in-utero exposure to more or less predictable floods might be attributed to districts that are non-common between subsamples. I verified that this is not the case by restricting the 1982-1983 and the 1997-1998 sub-samples to districts that overlap (1400 districts). My main results still hold and they are robust to the change in the sample.

[27] The households selected were those with both the head and spouse/wife living together.

Table 2.1: Summary Statistics

	All				
Covariate	N	Mean	Sd	Min	Max
Years of education	35622	11.74	(3.16)	1	18
Primary Educ Completion	36053	0.95	(0.22)	0	1
Secondary Educ Completion	36053	0.79	(0.41)	0	1
Age	36057	25.52	(4.58)	17	43
Urban	36057	0.84	(0.37)	0	1
Is Female	36057	0.47	(0.50)	0	1
Net HH income per capita (monthly)	36057	525.34	(595.14)	0	12291.29
Spanish mother tongue	21747	0.93	(0.26)	0	1
Household Size	36057	6.50	(2.32)	3	25
Married	36047	0.13	(0.33)	0	1
Mestizo (race)	19714	0.58	(0.49)	0	1
Treatment in utero*	36057	0.08	(0.27)	0	1
Treatment after birth*	36057	0.18	(0.39)	0	1
Intensity shock in-utero* (if Treatment in utero==1)	3487	2.10	(1.47)	1	6
Intensity early life shock* (if Treatment after birth ==1)	7950	2.27	(1.77)	1	6

Notes: *Exposure to the 1982-1983 El Niño.

Table 2.1 and Table 2.2 show descriptive statistics of individuals born between 1975 and 1983. On average, individuals have 12 years of education and 79% (95%) of them have completed high school (primary school). 47% of the sample are women and 13% reported to be married. 84% of the individuals in the sample are living in urban areas.[28] Moreover, individuals in the sample are on average 26 years old and 93% of them reported Spanish as a mother tongue. The average household's size is 7 members. 8% of individuals were exposed to floods that happened during 1982-1983 while in-utero, and the average length of exposure while in-utero was 2 months. Similarly, 18% of respondents experienced the event during early childhood (0-2 years old) with an average length of exposure of also 2 months. Table 2.2 shows differences in demographic characteristics by zone of residence (urban versus rural). Individuals in rural zones complete fewer years of education than their peers in urban zones. The average years of education in rural and urban zones in the sample is 9 and 12 years, respectively. While almost all individuals aged 17 years old or older, and

[28] The urban area is defined by INEI as communities with at least 100 dwellings grouped contiguously (on average 500 inhabitants). As an exception, the capital of districts is considered an urban area even when it does not meet this requirement. 34% of the individuals in the sample are classified as poor. INEI classifies a household as poor based on the line of poverty methodology by selecting a welfare indicator (per capita expenses) and a poverty threshold following the rule: i) The household is poor when per capita expenses are less than the poverty cutoff, and ii) the household is classified as non-poor when per capita expenses are equal or higher than the poverty line. Similarly, extreme poverty condition is defined based on the level of expenditure and the poverty cutoff. To establish the poverty line INEI uses a basket of basic goods and services for consumption, and the poverty line is the money needed to acquire this basket of goods and services.

who live in urban areas have completed primary education (97%), 81% of people similar in age in rural zones reported the same. Secondary completion rates are lower with 86% of individuals in urban areas and 45% of individuals in rural areas having completed secondary education. Net household monthly income per capita in urban and rural areas is 593 soles (USD 144) and 174 soles (USD 42), respectively, this confirms the presence of economic inequality in Peru. Individuals from rural areas have access to lower opportunities, and average net household income is more than three times higher in urban households.

Table 2.2: Summary Statistics by Zone of Residence

	Urban					Rural				
Covariate	N	Mean	Sd	Min	Max	N	Mean	Sd	Min	Max
Years of education	27420	12.28	(2.76)	1	18	8202	8.92	(3.62)	1	17
Primary Educ Completion	27593	0.97	(0.16)	0	1	8460	0.81	(0.39)	0	1
Secondary Educ Completion	27593	0.86	(0.35)	0	1	8460	0.45	(0.50)	0	1
Age	27596	25.78	(4.58)	17	43	8461	24.19	(4.35)	17	42
Is Female	27596	0.48	(0.50)	0	1	8461	0.41	(0.49)	0	1
Net HH income per capita (monthly)	27596	593.14	(621.09)	0	12291.29	8461	173.76	(207.61)	6.05	7782.6
Spanish mother tongue	16949	0.96	(0.19)	0	1	4798	0.71	(0.45)	0	1
Household Size	27596	6.38	(2.27)	3	25	8461	7.10	(2.46)	3	20
Married	27589	0.12	(0.33)	0	1	8458	0.14	(0.35)	0	1
Mestizo (race)	15269	0.60	(0.49)	0	1	4445	0.45	(0.50)	0	1
Treatment in utero*	27596	0.07	(0.25)	0	1	8461	0.12	(0.33)	0	1
Treatment after birth*	27596	0.17	(0.37)	0	1	8461	0.26	(0.44)	0	1
Intensity shock in-utero* (if Treatment in utero==1)	2455	2.18	(1.54)	1	6	1032	1.86	(1.21)	1	6
Intensity early life shock* (if Treatment after birth ==1)	5758	2.33	(1.83)	1	6	2192	2.09	(1.54)	1	6

Notes: *Exposure to the 1982-1983 El Niño.

2.4 Empirical Model

In this section, I describe the econometric model of the relationship between exposure to floods and long-term outcomes. For the identification, I exploit the 1982-1983 and the 1997-1998 El Niño in Peru as a natural experiment, and I use two sources of variation: i) cohort variation, ii) geographic variation.

$$Y_{idcps} = \alpha_1 treatment\_inutero_{idc} + X_{idcps}\alpha_g + \delta_c + \omega_d + \lambda_s + \gamma_p + \varepsilon_{idcps} \tag{2.3}$$

$$Y_{idcps} = \beta_1 shock\_inutero_{idc} + X_{idcps}\beta_g + \delta_c + \omega_d + \lambda_s + \gamma_p + u_{idcps} \tag{2.4}$$

Where i indexes the individual, d corresponds to the individual's district of birth, c indexes cohort of birth, p represents the province of residence, and s the survey year. Y is a dummy variable that equals one if the individual i answering survey s, living in province p, born in district d and at date c (quarter and year of birth) has completed primary education,[29] and zero otherwise. X is a vector of individual and socio-demographic characteristics. Regressions control for gender, age, and urban sector. The variable $shock\_inutero_{idc}$ in equation (2.4) measures the number of months of floods during 1982-1983 (1997-1998) El Niño experienced in-utero, and it is calculated based on the individual's district and date of birth. β_1 measures the effect of one additional month of exposure to El Niño floods while in-utero on primary education completion. Similarly, $treatment\_inutero_{idc}$ in equation (2.3) is the treatment variable which equals one if the individual was exposed to a flood while in-utero, and zero otherwise. α_1 indicates the effect of in-utero exposure to the 1982-1983 (1997-1998) El Niño on the likelihood of having completed primary education. While equation (2.3) explores the treatment effect, equation (2.4) analyzes the marginal effect of the event on educational outcomes.

The cohort fixed effects, δ_c, controls for any shock common to all individuals born in the same cohort. For example, it could be possible that individuals born in the second half of the year are more resilient towards climate change. Seasonal events at the time of birth (other shocks different from the 1982-1983 El Niño) could have impacted individuals' development. By controlling for cohort fixed effects I account for these unobserved effects on educational outcomes. Additionally, ω_d controls for the district of birth fixed effects, γ_p accounts for the province of residence fixed effects, and λ_s is the survey year fixed effect. ω_d and γ_p fixed effects account for local-specific characteristics that are invariant over time (such as social norms affecting the educational achievement of individuals in certain areas), and λ_s fixed effects control for survey year-specific factors that are

[29] Alternatively, I explore the effect of exposure to the 1982-1983 El Niño on secondary education completion.

common to all districts at the time of a survey that could affect survey outcomes. Finally, ε_{idcps} and u_{idcps} are the error terms. Standard errors are clustered at the district of birth level allowing the error terms to be correlated within each district.[30]

To consistently estimate causal effects of in-utero exposure to El Niño floods on individual outcomes (α_1), the main identification assumption requires the error term ε_{idcps} not to be correlated with the exposure measure, after controlling for fixed effects, and a set of observed characteristics X_{idcps}. In other words, my identification strategy of the causal effect of rainfall variation on education completion relies on the assumption that, conditional on several fixed effects, temporary rainfall deviations from the historical averages are uncorrelated with other latent determinants of education completion during gestation and through adulthood. A potential concern arises if districts that were affected by the 1982-1983 (1997-1998) El Niño had different pre-trends in the level of education of their residents compared to districts in the control group, under this case the identification assumption will not hold. One way to test for this assumption is by the assessment of pre-shock trends on educational outcomes and to see whether or not there is an association between in-utero exposure to El Niño floods and educational trends before the shock. Unfortunately, I cannot test for pre-shock trends because educational outcomes are not available before the El Niño event. However, I expect the evolution of educational outcomes to be very similar in control and treatment districts.

The main specification considers flood exposure while in-utero rather than exposure after birth (i.e. first or second year of life) because it has been demonstrated in previous studies that only exposure to shocks while in-utero has negative and significant effects on long-term outcomes such as children's academic performance.[31] In addition, I have explored exposure to 1982-1983 El Niño early in life as regressor (for children up to two years old), and results are not statistically significant for flood exposure after the birth year.

[30] I compare the main specifications (equation 2.3 and equation 2.4) with alternatives that account for household fixed effects as well, to comment on how results change depending on specific characteristics of the households. The results are available upon request.

[31] See for instance, [5], [7], and [55].

2.5 Results

2.5.1 The Effect of the 1982-1983 El Niño: Educational Outcomes

In this section, I present the results of in-utero exposure to the 1982-1983 El Niño on long-term outcomes following the specification in equation (2.3).

Table 2.3 shows the treatment effects estimates of in-utero exposure to the 1982-1983 El Niño on the probability to have completed primary education for individuals born between 1975 and 1983, and who are 17 years old or older. Odd columns do not account for control variables.[32] The results show that this subsample of individuals born between 1975 and 1983 was not significantly affected by the floods. The estimates are not statistically significant and close to zero (see Panel A, Table 2.3). In Peru, there is a lack of educational opportunities, specially for those individuals located in marginalized regions in rural zones. Therefore, the effect of in-utero exposure to El Niño might be different depending on the place of residence. Furthermore, rural and urban areas' adaptation to floods, resilience to natural phenomenons and quality of infrastructure could play a role in how well these areas face disasters.

In Panel B and Panel C of Table 2.3, I split the sample by zone of residence. The 1982-1983 event did not significantly affect primary education completion rates during adulthood for those individuals exposed to the shock in-utero and living in rural areas at the time of the survey. The no significant effect found in rural zones may be because individuals in rural zones have already low primary education completion rates (18% and 3% of individuals in rural and urban areas do not complete primary education). In contrast, individuals living in urban areas were significantly impacted by the event. In urban areas, individuals older than 17 years old and who were exposed to the 1982-1983 El Niño have 1.5 percentage points (significant at 5%) less probability to have completed primary education. The estimates are robust to the inclusion of covariates.

[32] Columns 2 and 4 in Table 2.3 show the effect of in-utero exposure to the 1982-1983 El Niño on primary education completion rates including covariates. I control for gender, age, and urban zone indicator.

Table 2.3: The Effect of In-Utero Exposure to 1982-1983 El Nino Shock on Primary Education Completion

Dep. Variable:	**Primary Education Completion**			
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
treatment_inutero	-0.00363	-0.00311	-0.00354	-0.00316
	(0.00769)	(0.00763)	(0.00737)	(0.00729)
Number of observations (N)	36,053	36,053	36,053	36,053
Adjusted R^2	0.173	0.186	0.173	0.186
Mean Dv (dependent variable) (Treatment==0)	0.95	0.95	0.95	0.95
Panel B: Urban				
treatment_inutero	-0.0147**	-0.0147**	-0.0146**	-0.0147**
	(0.00646)	(0.00645)	(0.00606)	(0.00605)
Number of observations (N)	27,593	27,593	27,593	27,593
Adjusted R^2	0.094	0.094	0.093	0.093
Mean Dv (dependent variable) (Treatment==0)	0.97	0.97	0.97	0.97
Panel C: Rural				
treatment_inutero	0.0235	0.0287	0.0235	0.0270
	(0.0297)	(0.0296)	(0.0283)	(0.0282)
Number of observations (N)	8,460	8,460	8,460	8,460
Adjusted R^2	0.181	0.197	0.180	0.197
Mean Dv (dependent variable) (Treatment==0)	0.81	0.81	0.81	0.81
Cohort of Birth FE	Yes	Yes	No	No
Month of Birth FE	No	No	Yes	Yes
Year of Birth FE	No	No	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: This table reports the treatment effects estimates on primary education completion for individuals born between 1975-1983. Column 1 and Column 3 show the estimates without control variables while control variables are added in Column 2 and Column 4. Each regression includes survey-year fixed effect, district of birth fixed effect, and province of residence fixed effect. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

In Table 2.4, I investigate the effect of in-utero exposure to the 1982-1983 El Niño on secondary education completion. For the full sample of individuals born between 1975-1983 and who are older than 17 years old, the 1982-1983 El Niño did not affect their probability to have completed secondary education (see Panel A, Table 2.4). Similarly, I explore heterogeneous effects by zone of residence on secondary education completion rates in Panel B and C. While in-utero exposure to the 1982-1983 El Niño seems not to have affected secondary education completion rates in urban areas, the probability to complete secondary education increases by 9 percentage points (significant at 5%), for individuals living in rural areas and exposed to the 1982-1983 El Niño. The estimates remain stable after controlling for covariates. Recall that the average rate of high school completion in the subsample is 46 percent for members of rural zones, so this is equivalent to a 20% increase.[33] It would be important to understand why the 1982-1983 El Niño had opposite effects on long-term outcomes, education completion rates in rural and urban zones. However, because of data limitations, this study cannot clearly identify possible mechanisms of this observed heterogeneity. One possible mediator could be the effect on crop production. Households in rural areas depend on agriculture, therefore, a high intake of rain can have positive effects on household income in rural zones with further implications for educational outcomes.

Finally, I also explore the effect of in-utero exposure to the 1982-1983 El Niño floods on total years of education completed. The results show that prenatal exposure to floods increases total years of education by 7-8 months in rural areas only. Given that the average total years of education in the control group and rural area is 9 years (less than secondary education), this corresponds to an increase of 7.2% (see Panel C, Table 2.5).

[33] At the baseline (treatment=0), 46% of individuals in rural areas have completed high school.

Table 2.4: The Effect of In-Utero Exposure to 1982-1983 El Nino Shock on Secondary Education Completion

Dep. Variable:	**Secondary Education Completion**			
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
treatment_inutero	-0.00216	-0.00241	-0.00183	-0.00229
	(0.0132)	(0.0129)	(0.0126)	(0.0123)
Number of observations (N)	35,977	35,977	35,977	35,977
Adjusted R^2	0.237	0.266	0.237	0.266
Mean Dv (Treatment==0)	0.80	0.80	0.80	0.80
Panel B: Urban				
treatment_inutero	-0.0165	-0.0176	-0.0151	-0.0161
	(0.0144)	(0.0144)	(0.0141)	(0.0142)
Number of observations (N)	27,543	27,543	27,543	27,543
Adjusted R^2	0.149	0.151	0.148	0.151
Mean Dv (Treatment==0)	0.87	0.87	0.87	0.87
Panel C: Rural				
treatment_inutero	0.0918**	0.0949***	0.0821**	0.0845**
	(0.0359)	(0.0357)	(0.0348)	(0.0346)
Number of observations (N)	8,434	8,434	8,434	8,434
Adjusted R^2	0.234	0.237	0.233	0.236
Mean Dv (Treatment==0)	0.46	0.46	0.46	0.46
Cohort of Birth FE	Yes	Yes	No	No
Month of Birth FE	No	No	Yes	Yes
Year of Birth FE	No	No	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: This table reports the treatment effects estimates on secondary education completion for individuals born between 1975-1983. Column 1 and Column 3 show the estimates without control variables while control variables are added in Column 2 and Column 4. Each regression includes survey-year fixed effect, district of birth fixed effect, and province of residence fixed effect. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 2.5: The Effect of In-Utero Exposure to 1982-1983 El Nino Shock on Total Years of Education

Dep. Variable:	**Years of Education**			
	(1)	(2)	(3)	(4)
Panel A: Full Sample				
treatment_inutero	0.00609	0.000587	0.0256	0.0177
	(0.109)	(0.106)	(0.104)	(0.102)
Number of observations (N)	35,622	35,622	35,622	35,622
Adjusted R^2	0.282	0.315	0.282	0.314
Mean Dv (Treatment==0)	11.83	11.83	11.83	11.83
Panel B: Urban				
treatment_inutero	-0.158	-0.170	-0.125	-0.138
	(0.116)	(0.115)	(0.113)	(0.112)
Number of observations (N)	27,420	27,420	27,420	27,420
Adjusted R^2	0.200	0.205	0.199	0.204
Mean Dv (Treatment==0)	12.33	12.33	12.33	12.33
Panel C: Rural				
treatment_inutero	0.613***	0.647***	0.558**	0.585**
	(0.236)	(0.235)	(0.230)	(0.229)
Number of observations (N)	8,202	8,202	8,202	8,202
Adjusted R^2	0.279	0.285	0.278	0.284
Mean Dv (Treatment==0)	8.98	8.98	8.98	8.98
Cohort of Birth FE	Yes	Yes	No	No
Month of Birth FE	No	No	Yes	Yes
Year of Birth FE	No	No	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: This table reports the treatment effects estimates on total years of education for individuals born between 1975-1983. Column 1 and Column 3 show the estimates without control variables while control variables are added in Column 2 and Column 4. Each regression includes survey-year fixed effect, district of birth fixed effect, and province of residence fixed effect. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 2.6: The Effect of In-Utero Exposure to 1997-1998 El Nino Shock on Education Outcomes

Sample:	Full	Full	Urban	Urban	Rural	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Primary Education Completion						
treatment_inutero	0.00808	0.00774	0.0118*	0.0118*	-0.0136	-0.0161
	(0.00593)	(0.00592)	(0.00685)	(0.00685)	(0.0144)	(0.0143)
Number of observations (N)	58,367	58,367	39,136	39,136	19,231	19,231
Adjusted R^2	0.072	0.076	0.065	0.065	0.080	0.084
Mean Dv (Treatment==0)	0.97	0.97	0.98	0.98	0.93	0.93
Panel B: Secondary Education Completion						
treatment_inutero	-0.0193	-0.0200	-0.00758	-0.00524	-0.0739*	-0.0767*
	(0.0214)	(0.0216)	(0.0257)	(0.0259)	(0.0442)	(0.0447)
Number of observations (N)	46,408	46,408	31,972	31,972	14,436	14,436
Adjusted R^2	0.178	0.199	0.100	0.104	0.195	0.196
Mean Dv (Treatment==0)	0.84	0.84	0.90	0.90	0.62	0.62
Panel C: Total Years of Education						
treatment_inutero	0.0421	0.0425	0.0515	0.0547	0.0513	0.0516
	(0.0333)	(0.0333)	(0.0375)	(0.0375)	(0.0551)	(0.0552)
Number of observations (N)	169,837	169,837	100,106	100,106	69,731	69,731
Adjusted R^2	0.833	0.836	0.856	0.856	0.754	0.754
Mean Dv (Treatment==0)	7.38	7.38	7.99	7.99	5.98	5.98
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

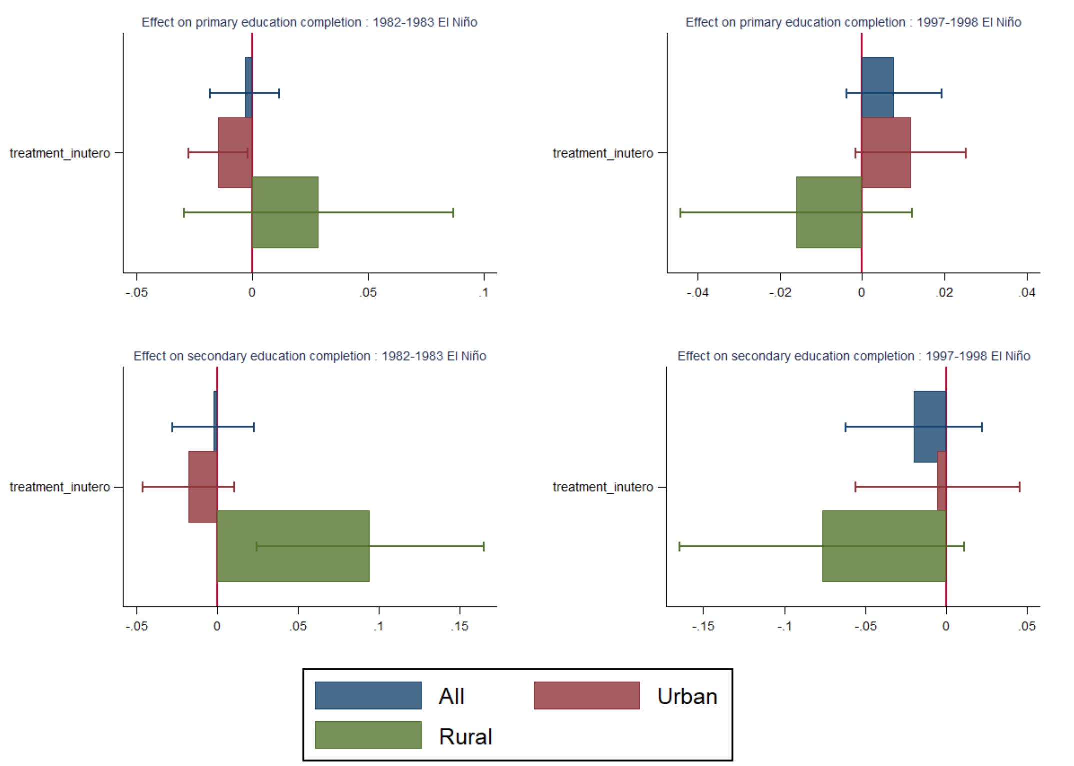
Notes: This table reports the effect of in-utero exposure to the 1997-1998 El Niño on long-term education outcomes for individuals born between 1990-1998. The variable treatment_inutero equals one if the individual was exposed to the 1997-1998 El Niño while in-utero, and zero otherwise. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

2.5.2 The Effect of the 1997-1998 El Niño: Educational Outcomes

In this section, I investigate the effect of a more predictable El Niño (1997-1998) on educational outcomes following equation (2.3). Panel A of Table 2.6 reports the estimates on the probability to complete primary education for the full sample of individuals older than 16 years old and who were born between 1990-1998. The estimates are not statistically significant and at most, they are marginally significant at 10% level (see columns 3 and 4, Table 2.6). In addition, Panel B of Table 2.6 shows the effect of in-utero exposure to the 1997-1998 El Niño on secondary education completion. The more predictable El Niño did not have an impact on secondary completion rates in urban zones or for the full sample of individuals. In rural zones, the estimate is negative and marginally significant at 10%. Individuals aged 18 years or older, in rural areas and exposed to floods while in-utero have 7-8 percentage points less probability to complete secondary education.[34] Finally, I evaluate the effect of the floods on total years of education, and the estimates remain statistically insignificant. To summarize the main results, Figure 2.4 shows the point estimates of prenatal exposure to a more and a less predictable El Niño by zone of residence, and 95% confidence intervals. While in-utero exposure to a less predictable El Niño of 1982-1983 had significant effects on long-term educational outcomes, an exposure to a more predictable El Niño of 1997-1998 did not affect the education achievement of individuals during adulthood.

[34] The population is still too young to have completed secondary education by the time of the survey. Moreover, the less precise estimates respond to the less variability in treatment status.

Figure 2.4: Effect of Exposure to a More Predictable and a Less Predictable El Niño on Long-Term Education Outcomes



Notes: This figure shows the point estimates of in-utero exposure to El Niño floods on long-term education outcomes: i) primary education completion, ii) secondary education completion following equation (2.3). Horizontal spikes denote 95% confidence intervals.

Table 2.7: The Effect of Intensity of El Niño (1982-1983) on Long-Term Education Outcomes

Sample:	Full	Full	Urban	Urban	Rural	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Primary Education Completion						
shock_inutero	-0.00150	-0.00175	-0.00691**	-0.00691**	0.0228*	0.0251*
	(0.00338)	(0.00331)	(0.00292)	(0.00292)	(0.0132)	(0.0131)
Number of observations (N)	36,053	36,053	27,593	27,593	8,460	8,460
Adjusted R^2	0.173	0.186	0.094	0.094	0.181	0.198
Panel B: Secondary Education Completion						
shock_inutero	0.00540	0.00436	-0.000179	-0.000381	0.0360***	0.0373***
	(0.00478)	(0.00449)	(0.00476)	(0.00473)	(0.0136)	(0.0136)
Number of observations (N)	35,977	35,977	27,543	27,543	8,434	8,434
Adjusted R^2	0.238	0.266	0.149	0.151	0.234	0.237
Panel C: Total Years of Education						
shock_inutero	0.0145	0.00510	-0.0484	-0.0512	0.290***	0.303***
	(0.0381)	(0.0362)	(0.0361)	(0.0353)	(0.106)	(0.104)
Number of observations (N)	35,622	35,622	27,420	27,420	8,202	8,202
Adjusted R^2	0.282	0.315	0.200	0.205	0.280	0.286
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: This table reports the effect of intensity of exposure to the 1982-1983 El Niño on long-term education outcomes for individuals born between 1975-1983. The treatment variable is the number of months of exposure to intense floods. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

2.5.3 The Intensity of Exposure to the 1982-1983 El Niño

In the previous section, I evaluated the effect of at least one month of exposure to floods during pregnancy on long-term outcomes. While the treatment dummy variable reflects the effect of exposure to a flood while in-utero, it would be interesting to also explore the marginal effect of the event on educational outcomes (see equation 2.4). Panel A of Table 2.7 shows that one additional month of exposure to floods while in-utero reduces the probability that the individual has completed primary education by 0.69 percentage points (significant at 5%) in urban areas. In contrast, in rural areas, the estimates are imprecise and the effect is positive but marginally significant at 10%. Panel B of Table 2.7 reports the estimates on secondary education completion. Different from the results found for primary education completion rates, one additional month of in-utero exposure to the 1982-1983 El Niño increases the chance to complete secondary education by 4 percentage points (significant at 1%) and for the subgroup of individuals living in rural dwellings. Similarly, I found that in rural areas, individuals exposed to one additional month of floods before birth date have completed 4 additional months of education than their peers (see Panel C of Table 2.7). It would also be interesting to investigate why exposure to the 1982-1983 El Niño floods negatively affected primary education completion in urban areas but it had a positive and significant effect on total years of education in rural zones and on secondary education completion rates. The heterogeneous effects by place of residence suggest that the 1982-1983 El Niño impacted living conditions around the time but the effects and magnitude of the event were not the same in rural and urban locations.[35]

2.5.4 The Intensity of Exposure to the 1997-1998 El Niño

Similar to the previous section, I assess the marginal effect of in-utero exposure but rather than exploring the variation of exposure to the 1982-1983 El Niño, I investigate the extent to which a less predictable phenomenon, the 1997-1998 El Niño, could have affected educational outcomes. At first glance, the results show that a more predictable El Niño could have a positive effect on the

[35] Unfortunately, ENAHO does not have detailed information to explore possible mechanisms at this time. In future projects, I would explore possible mechanisms using administrative data of the Peruvian Education Office and students' academic performance.

probability to complete more years of education and primary education. For instance, individuals exposed by one additional month to the 1997-1998 floods are more likely to have completed primary education during adulthood by 0.71 percentage points (significant at 1%).[36] Moreover, one additional month of exposure to floods during the 1997-1998 phenomenon increases total years of education by 2.9 percentage points (significant at 10%). The effect is driven by individuals living in urban areas (3.7 percentage points, significant at 5%).[37]

2.5.5 El Niño and its effects on other outcomes

The effect of in-utero exposure to extreme weather conditions can have additional effects on other outcomes such as health and income. In Tables A1 and A2, in the Appendix, I explore the effect of the 1982-1983 and the 1997-1998 El Niño on other outcomes during adulthood such as self-employment status, marital status, poverty condition, and the probability to have a chronic disease. Table A1 shows that prenatal flood exposure to the 1997-1998 El Niño had long-term negative effects on health outcomes during adulthood. Individuals who experienced prenatal exposure to floods are more likely to have a chronic disease later in life (2.4 percentage points, significant at 5%). In contrast, the estimates on income variables remain statistically insignificant. The increase in the probability to develop a chronic disease affects those living in urban areas but does not impact the health conditions of people in rural zones.[38]

[36] See for instance Table 2.8.

[37] See for example column 3-4, Panel C of Table 2.8.

[38] The main objective of this study is not to analyze the underlying mechanisms of in-utero exposure to El Niño floods on education outcomes. However, since I found no effects for exposure to extreme weather conditions during early life (0-2 years old), I suspect the "Fetal Origins" hypothesis plays an important role in the Peruvian context. The period of gestation has significant impacts on the individual well-being and health. During the 1982-1983 event the supply of food was affected due to the destruction of roads, infrastructure, lack of transportation, and the increase in the volume of water of the main rivers. The lack of food could have affected the food intake of pregnant women.

Table 2.8: The Effect of Intensity of El Niño (1997-1998) on Long-Term Education Outcomes

Sample:	Full	Full	Urban	Urban	Rural	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Primary Education Completion						
shock_inutero	0.00711***	0.00709***	0.00828***	0.00840***	-0.00434	-0.00503
	(0.00256)	(0.00254)	(0.00273)	(0.00273)	(0.00695)	(0.00692)
Number of observations (N)	58,367	58,367	39,136	39,136	19,231	19,231
Adjusted R^2	0.072	0.076	0.065	0.065	0.080	0.084
Panel B: Secondary Education Completion						
shock_inutero	0.00495	0.00529	0.0112	0.0129	-0.0330	-0.0336
	(0.0102)	(0.0102)	(0.0120)	(0.0120)	(0.0300)	(0.0305)
Number of observations (N)	46,408	46,408	31,972	31,972	14,436	14,436
Adjusted R^2	0.178	0.199	0.100	0.104	0.195	0.195
Panel C: Total Years of Education						
shock_inutero	0.0282	0.0289*	0.0356*	0.0375**	0.0170	0.0173
	(0.0172)	(0.0167)	(0.0183)	(0.0183)	(0.0306)	(0.0306)
Number of observations (N)	169,837	169,837	100,106	100,106	69,731	69,731
Adjusted R^2	0.833	0.836	0.856	0.857	0.754	0.754
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: This table reports the effect of intensity of exposure to the 1997-1998 El Niño on long-term education outcomes for individuals born between 1990-1998. The treatment variable is the number of months of exposure to intense floods. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

2.5.6 Early in life exposure to the 1982-1983 El Niño

Previous studies have argued that early in life exposure to natural disasters and extreme weather conditions can have long-term effects on children's development. In this section, I investigate the effect of exposure to the Niño event after birth on long-term educational outcomes. Different from in-utero exposure to floods, an early in life exposure to floods does not have an effect on the probability that adults have completed primary (secondary) education (See Table A3 and A4, Appendix).[39]

2.5.7 Family Background

Unobserved households' characteristics could determine children's education outcomes. For example, parents with a high level of education are more likely to prioritize the education of children. Therefore, I expect children born in families where parents are highly educated to be less impacted by in-utero exposure to the 1982-1983 El Niño. To overcome this issue, I include household fixed effects in the regressions. After the inclusion of household fixed effects, the negative estimates of in-utero exposure to the event on primary education completion are not significant anymore. Moreover, the treatment effect estimates on secondary education completion become insignificant. Thus, this might suggest that household unobserved characteristics explain the level of education completed by children in the household.

2.5.8 Transmission Channels

In this section, I discuss possible mechanisms that can explain the impact of pre-natal shock on human capital development. One mechanism is through the effect on human brain development (biological channel), which starts in the first trimester of pregnancy. In addition, shocks generate maternal stress during the pre-natal period and can play an important role in the infant behavior later in life. Another channel is the nutritional channel. For instance, unexpected variation in rainfall can affect long-term education outcomes through an impact on yields and consumption.

[39] Similarly, early in life exposure to the 1997-1998 El Niño does not affect primary education completion rates during adulthood. The results are available upon request.

This is particularly important in developing countries and in rural areas where families live out of what they produce and agriculture is their main economic activity. Notice that the effect on crop production varies depending on the type of crop, the usage of technology, and the ability to predict weather conditions. A negative impact on crop production, yields, and consumption can decrease the mother's consumption of nutrients during pregnancy with further implications on weight at birth of the newborn and human capital development.

2.6 Robustness Checks and Heterogeneous Effects

2.6.1 Robustness Checks

Balance Test

A potential threat to the identification assumption is that the exposure to El Niño floods may be confounded by similar unobserved characteristics that vary across districts and over time. It could be possible that the exposure to El Niño floods captures any changes in demographic characteristics of households giving birth in more affected municipalities rather than the exposure to the shock itself.

In order to check this selection problem, I test for balance in covariates between the treatment and the control groups by regressing each of the covariates on the treatment variable controlling for fixed effects and clustering the standard errors at the district of birth. The results show no significant differences in most demographic and individual characteristics between treatment and control groups. (see Table A5-A6, in the Appendix). Except for individuals' age and gender, and parental education, there are no differences in covariates between those exposed and those not exposed to the floods. I control for age and gender in the specifications and I evaluate heterogeneous effects of the event on educational outcomes by dividing the sample based on parental education.[40] The results are robust to the inclusion of covariates.

[40] In families where the parents reported not to have completed secondary education, the in-utero exposure of the children to the 1982-1983 El Niño reduced the probability that the children complete primary education later in life. In contrast, I do not find significant effects on primary education completion in families where parents reported to have completed secondary education.

Falsification Test

The main identifying assumption to consistently estimate the causal effect of in-utero exposure to El Niño floods on educational outcomes requires the treatment and the error term not to be correlated, after controlling for fixed effects and control variables. Unfortunately, I cannot test for pre-event trends on educational outcomes for treatment and control districts because survey data on educational outcomes do not exist before 1982-1983. Furthermore, it could be possible that the negative effects of in-utero exposure to the El Niño flood on education completion may be confounded with omitted variables. To verify this is not the case, placebo regressions are estimated using the sample of individuals born between 1985 and 1988. I replicate the geographic intensity of the 1982-1983 shock using a different period, 1985-1986.[41] Then, I proceed to generate the dummy for treatment in-utero, and the exposure to the shock (intensity-in number of months exposed to floods while in-utero). The treatment dummy takes the value of one whenever the individual was exposed to floods at least one month while in-utero between December 1985 and June 1986, and zero otherwise. Since these individuals are part of the comparison group, this placebo test is key to validate that there are no different trends between locations affected and not affected by the floods for individuals that were not exposed to the 1982-1983 El Niño. I do not observe statistically significant estimates in the placebo regressions. The construction of the treatment variable uses precipitation data of the nearest node to the center of the district where the individual was born.[42] I perform a falsification test by choosing a far node from the center of the district. Using nodes located in the 5th position or 10th position in a ranking from nearest (1st) to furthest node from the center of the district, the effect of exposure to floods while in-utero on the probability of secondary/primary education completion disappears.[43] The findings are robust to the inclusion of even far nodes. Finally, I use a probit model to estimate the effect of exposure to floods on the probability to complete secondary/primary education. The marginal effects are comparable in sign

[41] In particular, I restrict the period to December 1985-June 1986.

[42] The average minimum distance from the node to the center of the district is 22 km with a maximum distance of 50 km and a minimum distance of 1km.

[43] The node positioned in place 5 is located on average 70 km away from the center of the district where the individual was born, with a minimum distance of 56 km and a maximum distance of 107 km. Similarly, the node positioned in place 10 is located on average 101 km from the center of the district with a minimum of 87 km and a maximum of 157 km.

and size to the estimates using a linear probability model.[44]

2.6.2 Heterogeneous Effects

Trimester of Pregnancy: The exposure to extreme weather conditions can affect individuals' outcomes differently depending on the trimester of pregnancy. Some studies have suggested that extreme weather conditions in the first trimester, when the major organs form, could contribute to certain birth defects, whereas exposure in the second or third trimester, when the fetus undergoes rapid growth, may contribute to preterm birth, low maternal weight gain, and a significantly greater risk of intrauterine growth retardation. I verify in which trimester of pregnancy an in-utero exposure to the Niño has strong effects on educational outcomes. The results suggest that one additional month of exposure to the 1982-1983 El Niño in the second or third trimester reduced the probability that the individual has completed primary education, and the results are significant for those living in urban dwellings.

Exposure to El Niño by gender: In this section, I explore whether an in-utero exposure to El Niño has different effects on education outcomes by gender. It could be the case that women and men are differently affected by the event. In order to test for it, I estimate equation (2.3) and (2.4) separately for women and men. The effects of a prenatal exposure to El Niño floods on primary education completion are statistically significant for men but not for women. For example, one additional month of in-utero exposure to the 1982-1983 floods decreased the probability that boys who were exposed to the floods and living in urban areas have completed primary education by the age of 17 years old. My findings are according to previous evidence suggesting that for health and education outcomes, boys are disadvantaged when affected in utero or early life due to biological factors. In addition, if labor needs increase following exposure to floods, boys are more likely to be taken out of schools to work in the agricultural sector.

Grouping by Parental Education: If more disadvantaged families fail to adequately cope with extreme weather conditions, it is plausible that the effect of exposure to the Niño floods on later human capital outcomes is stronger for less-educated families, suggesting that prenatal shocks might

[44] The results are available upon request.

exacerbate pre-existing inequalities. In this section, I proceed to divide the sample into two groups: i) individuals with parents who have not completed secondary education, ii) individuals with parents who have at least completed secondary education at the time of the survey. Then, I explore the effect of in-utero exposure to the 1982-1983 and 1997-1998 El Niño on education outcomes, separately for these two groups. The results suggest that the effects are negative and statistically significant for primary education completion of the individual when the individual's father reported not to have completed secondary education. Alternatively, I estimate my baseline equation (2.3) but include an interaction term to verify how an in-utero exposure to the 1982-1983 El Niño affects primary education completion differently for individuals with parents who have completed secondary education versus those with parents with incomplete secondary education. The estimates on both the interaction term and the treatment indicator are not statistically significant. On the other hand, the coefficient of the dummy for parental secondary education completion is positive and statistically significant. Thus, parental education plays an important role in determining children's ability to complete primary education.

2.7 Conclusion

This study shows evidence that the less predictable El Niño flood (1982-1983) generated long-term consequences on education outcomes of the Peruvian population that had experienced prenatal exposure to the floods. This adverse and unpredictable event, affecting the evolution of babies while in-utero, in particular during the nine months of gestation, reduced the probability that the exposed individual had completed primary education (by the time of 17 years old or older) in urban areas while the effects on rural zones were statistically insignificant. On the other hand, the same in-utero exposure but to a more predictable El Niño had opposite effects on education outcomes and most of the estimates were insignificant or marginal significant at the 10%. I find different estimates in terms of levels and significance if I replicate the same analysis using the El Niño event of 1997-1998, which was less intense and more anticipated according to reports of the National Meteorology and Hydrology Service of Peru. Thus, public policies oriented to protect pregnant women from adverse shocks such as pandemics, famine, and extreme weather conditions should direct funds towards the investment in the creation of knowledge and new technology to forecast the occurrence of these events.

A potential issue that could contaminate the estimates of the effect of in-utero exposure to El Niño floods on later outcomes is the fact that I only observe individuals who survived. If extreme El Niño floods increase neonatal and infant mortality, then the estimated effects could be downward biased due to selective mortality. The selective mortality problem has been discussed in previous literature and it refers to a sample selection issue given that weaker babies, in terms of health condition, should have been less likely to survive. In the context of the paper, this transmits in only observing individuals that had better health outcomes while in-utero. In particular, I evaluate the impact of the event on the population that could have survived due to a better allocation of resources and health status during the 1982-1983 El Niño. In the hypothetical case that I could have observed individuals that did not survive, then the impact of the event should be even more negative.[45]

For further research, I plan to evaluate possible channels that could explain why exposure to the 1982-1983 floods in-utero affected the formation of human capital, and the heterogeneous effects found by place of residence and predictability of the event. Also, while this study mainly looks at secondary and primary education completion rates, other outcomes could be evaluated following a similar approach (for example, test scores, academic performance).

Finally, it is important to remark the close connection between in-utero conditions of the baby from the first month of conception and the development of the individual later in life. This study suggests that it is impossible to separate what happens during the formation of the person while in-utero of the mother from the development of humans after birth.

[45] Using Peruvian Census data I calculated the size of selection mortality bias by counting the number of individuals who live in Treatment and Control districts for each cohort of birth, especially restricting cohorts to individuals up to 5 years old. The Census data also allows verifying whether the individual lives in the district where he/she was born. In the case individuals were not living in the place they were born, I know in which district the individual was born, and I use that information to compute the population. I proceed to perform a test of equality of means by treatment status. From the results of the test, I cannot reject the presence of selective mortality because the average population in treatment and control districts are very different, and the difference is statistically significant at the 5%.

3

To inspire and to inform: The role of role models[1]

3.1 Introduction

Despite significant progress in women's access to college education in recent decades, there is still a gender enrollment gap in Science, Technology, Engineering, and Mathematics (STEM) majors. Within STEM disciplines, women's participation in engineering, one of the primary STEM fields, remains significantly below that of males in both developing and developed countries. For instance, while in the 2017-18 academic year 57% of bachelor's degrees were conferred to women in the United States; just 13% of bachelor's degrees in engineering were awarded to females.[2] A recent report by [126] shows that in Latin American countries, such as Colombia and Mexico, the female participation rate in engineering majors is lower than 35%, and that worldwide, only 8% of the female student population choose engineering related fields of study. The gender participation gap in engineering has profound consequences for women in particular and society in general. It con-

[1] This chapter is part of a joint project with committee members Marcos Agurto, Siddharth Hari, and my advisor Sudipta Sarangi. This manuscript was previously published as a discussion paper. See for instance: Agurto, M.; Bazan, M.; Hari, S.; Sarangi, S. (2021) : Women in Engineering: The Role of Role Models, GLO Discussion Paper, No. 975, Global Labor Organization (GLO), Essen.

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

tributes to the under-representation of females at the top of the income distribution,[3] has negative effects for the development of new ideas, science, technology and firms productivity, and critical repercussions on economic growth via the misallocation of talent.[4]

The persistence of gendered paths in career choices reinforces the prevalence of negative stereotypes and beliefs about women's suitability for STEM fields. Women are not believed to be good at math, and therefore better suited for careers in the humanities or the social sciences. On the other hand, men are expected to be naturally good at math and to excel in engineering majors. Such beliefs further demotivate women from choosing careers according to their actual talent and abilities.[5]

Understanding the causes of low female participation in STEM fields continues to be an important research and policy question that has been studied by professionals in various fields. Several factors have been proposed as determinants of the observed gender STEM gap, such as differences in biological characteristics (brain structure), peer effects, individual preferences and beliefs, external validation, self-perception of ability, and social norms. With respect to differences in brain structure, there is a broad consensus that it does not account for the observed differences in math performance across genders, and that it is not related to the low enrollment of women in STEM careers [56], [105], [126]. Alternatively, other researchers have examined non-cognitive abilities (i.e. self-efficacy, self-perception) as potential drivers of the lack of women in STEM [46], [80]. Within STEM fields, the evidence strongly suggests that engineering has a low proportion of females mainly due to women's perception that engineering is a career not suitable for them [58]. Moreover, these stereotypes are transmitted to girls from a young age. Girls consider engineering as a "masculine" domain and believe that women cannot succeed there [111], as they lack the necessary skills as well

[3]See for instance [32] and [25].

[4]Detailed discussions can be found in [128], [17], [73], [57], [15], [75].

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

as due to the discrimination faced by women within STEM fields in the labor market [88], [33], [15]. Additionally, some authors point out the competitive nature in STEM fields as a reason for the low participation of women in Science and Engineering careers [69], [103], [104], [34], [63].

This paper addresses an important, yet under-studied factor that can play a key role in explaining the gender gap in STEM careers: the lack of appropriate female role models. Growing up, most of us have had that one person(s) we have looked up to, were inspired by, and hoped to emulate. However, several barriers restrict young girls from having female role models in STEM, such as their relative scarcity in many contexts, as well as the absence of initiatives that bring the experience of the few existing ones to young girls. It is therefore difficult for high school girls to come into direct contact with women who have majored or are majoring in STEM fields, such as engineering. Our intervention aims to alleviate this problem by bringing those relatively scarce role models close to high school girls.[6] We collaborated with a private elite university in Northern Peru, Universidad de Piura (UDEP),[7] in the context of a randomized controlled trial that provided role model talks to students in their last year of high school. Our role models were female senior college students or very recent graduates in engineering. We then evaluate the impact of our role models intervention on high school girls preferences towards STEM majors, in particular engineering ones.

Early studies that assess the effectiveness of role models on students' academic performance, students' enrollment, drop-out decisions and occupational choices within STEM majors mainly focused on the role of teachers or instructors.[8] However, many of these studies suffer from identification issues related to the unobserved preferences of instructors towards same gender students [129], as well as the self-selection of students choosing to attend classes with instructors who they like the most, or have less strict grading policies. Because of these constraints, causality cannot be clearly established. Our paper isolates the role model channel through random, exogenous, variation in

[6] Even though it would be interesting to randomize the gender of the role model students were exposed by including male role models, previous interventions have shown that only female role models can impact the aspirations and gender attitudes of both male and female students [83], [93].

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

[8] Although this is not an exhaustive list, a wide range of issues relevant to this aspect can be found in the papers by [38], [117], [101], [22], [48], [72], [41], [27], [54], [94], [84], and [95].

role model exposure, while focusing on female role models who are not instructors. Other studies have also analyzed the effects of non-teaching role model interventions in the field [[102], [16], [49], [10], [108], [29], [31], [87]].

Most closely related to our paper is a recent study by [108]. The authors assess the effect of simultaneous exposure to two female role models, who are professionals economists, on college freshman students' decisions to major in Economics. Each role model visit consisted of a 15-minute discussion about the role model's experiences as an economics major, career paths, and achievements. The authors show that a brief exposure to a female role model increases students' academic performance and influences their choice of major. Our study also investigates the effect of a brief role model exposure, but departs from [108] in several ways. Most importantly, our paper's goal is to understand the engineering related career choices of female high school students in a developing country where strong gender stereotypes are prevalent in engineering fields. This is significantly different from studying career choices of students already enrolled in college in a developed country and in non-engineering majors. Another experimental study also related to ours is the one by [29], [30]. In this study, female middle-age role models (i.e. scientists and PhD students) were able to influence French high school students' perception towards STEM fields. The classroom interventions in this study lasted one hour and consisted of a combination of videos and slides shown during the role model visits. A critical difference of our high school study context relative to that in [29], is that in Peru, as well as in many other developing countries, there is no science track that separates students as a function of their preferences or skills for science majors. Also importantly, the role models in our intervention are senior college students or very recent graduates in engineering, and therefore younger and closer in age to the target group than the role models in [29] and [108]. Therefore, we expect our role models not only to motivate high school students, but also high school students to feel more connected to them.

Our paper relates to three strands of the literature. Firstly, it adds to the extensive body of research on the causes of the STEM gender gap, particularly in engineering. There is a broad consensus that gender differences in brain structure are unlikely to explain this gap [76], [122]. In contrast, the literature points out to stereotypes and social norms as critical at influencing career choices and contributing to gender segregation across college majors. Our study shows that brief interactions with external (non-teaching) female students or recent graduates in engineering disciplines can influence girls' perceptions, self-confidence and ultimately their career preferences. Secondly, the paper contributes to studies in social psychology that look at the effect of gender stereotypes on women's under-representation in science [50]. Several studies in social psychology have analyzed mentoring programs and non-teaching role model interventions like [44] and [98], but have not been successful at tracking the causal effects on career choices and isolating the related mechanisms. Our paper fills this gap as well. Thirdly, different from a number of studies that investigate role model effects in non-face-to-face contexts (TV shows, inspirational videos shown to randomly selected individuals),[9] ours relies on direct communication between role models and the target population.

Our field experiment implemented classroom talks in which female senior college students or very recent graduates in engineering fields from UDEP, communicated and interacted with senior-year high school students in Northern Peru. We exploit this experimental setting to test whether exposure to female senior students/recent graduates in engineering acting as role models can change high school girls' engineering perceptions, self-confidence and ultimately increase the proportion of girls preferring engineering majors at college. Our main dependent variable is a binary indicator equal to one if the high school student plans to enroll in engineering at any higher education institution and zero otherwise. It was constructed from the students' responses to a follow-up survey administered six months after the role model visits to both treatment and control schools. Our total sample roughly contains 5,000 students in 11th grade, which is the final year of secondary education in Peru, and a period when most high school students start looking for higher education opportunities.

A key advantage of our intervention is that the role models are senior engineering students or recent engineering graduates with first-hand experience and knowledge on the skills, aptitude and motivation needed to pursue and successfully navigate the engineering studies at college. The role

[9] See for instance, [60], [112], [19], [82].

models were volunteers and received feedback from UDEP faculty members before talking to audiences made of male and female high school students. The task of the role models was to deliver a 20-minute motivational presentation in treatment schools and to answer questions thereafter. The role models provided information to students in selected schools based on a set of slides. Overall, the main message transmitted to students can be summarized in the following lines:

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

While some researchers suggest focusing attention on training programs offered to early age students, between 5-10 years old [120], in order to achieve stronger effects on students' career choices and gender stereotypes; we believe that interventions that target senior high school students, particularly female ones, are necessary and can make a difference. Firstly, making a career choice is an important decision that it is being constantly reevaluated by school age individuals; therefore, reinforcing interventions are indispensable. This issue becomes more salient in contexts like the Peruvian one, where females are constantly and heavily exposed to gender stereotypes through all their school years. Secondly, as mentioned earlier, the Peruvian educational system lacks a specific science track that segregates students within schools based on skills and preferences, neither at the basic nor high school levels of education. All students follow the same curriculum. Therefore, interventions that expose senior-year high school students to female role models may influence the career choices of students at the margin and could change students' perceptions.

Our results suggest that exposure to a female engineer role model can increase female high school students' preferences towards engineering majors. This effect is concentrated among high math ability girls, particularly those in high schools located geographically close to the role models university.[10] Being in a treated school increases the probability that a female student in the upper

[10]The presence of regional effects in role model interventions has already being pointed out by previous studies in the literature. [71] for example studies the effect of online mentoring programs at a public German university to improve online teaching effectiveness during COVID-19. The mentees in this study were undergraduate students enrolled in the second term, and mentors were more senior students but enrolled in the same study program as the mentees. The authors find that students

quartile of the baseline math score distribution and in schools located close to UDEP (Piura region), would plan to enroll in any type of engineering by 14.1 percentage points. This corresponds to a more than 77% increase in preferences for engineering in treatment schools compared to the control ones.[11] To our surprise, in some specifications we find weak evidence suggesting that boys in the two lowest math ability quartiles increase their preferences for engineering majors by 6 to 7 percentage points.

To shed light on the possible mechanisms underlying these results, we find that the treatment significantly increased high math ability girls self-confidence in their aptitude and skills to perform well in engineering majors. Moreover, the treatment increased their interest in the engineering majors of the role models. This points to role models as a source of inspiration. In the case of boys, the mechanisms are less clear; but the evidence suggests that they are related to the specific information provided in the talks, which stressed that skills other than math ability are also relevant in engineering majors. It is also important to highlight that our results related to preferences and potential mechanisms are stronger among students that reside within UDEP geographical area of influence. Taken together, all these suggest that not everyone can be an effective role model in any type of context.

3.2 Institutional context and experimental setting

In this section, we describe the educational setting and general context under which our experiment took place, as well as the details of the role models intervention.

3.2.1 High school setting and female under-representation in STEM

The school system in Peru consists of six years of elementary education followed by five years of secondary education. School attendance in the country is compulsory from ages 5 to 16. Approx-

who reside in the region where the university is located benefit more from the program. The mentoring program had positive effects on students' motivation, exam registrations, and academic performance.

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

imately 2.5 million students are enrolled at the high school level,[12] and 15,000 high schools are active across the 25 country regions.[13] At the high school level classes are usually administered by different instructors depending on the subject, and the school year runs from March to December.[14] While the government runs a public school system, for-profit and not-for-profit private schools also exist. The curriculum, which is defined by the Ministry of Education and must be followed by all schools in the country, does not distinguish between students who aim to pursue STEM and non-STEM college majors at any level of basic or high school education. Furthermore, Peru does not have a centralized university admission system and each university is responsible for its own admission process. In public universities, admission basically depends on a general examination test set by each university. In some private universities, other admission mechanisms are also present.[15] The schools in our intervention sample are located in 6 out of the 25 regions in Peru, all of them in the northern part of the country, as it can be observed in Figure A8 in the Appendix. Roughly 60% of the schools (64 schools) are in the Piura Region, where UDEP's main campus is located. Of the remaining schools in our sample, 11 schools are located in La Libertad, 12 in Cajamarca, 3 in Ancash, 12 in Lambayeque and 7 in Tumbes.

While STEM careers cover various disciplines, in Peru engineering is by far the preferred STEM program among high school graduates. During the period 2016-2017, 93% of the roughly 417,000 students who applied for admission into a STEM field did so in engineering.[16] As in other countries around the world and in the Latin American region, in Peru, females are underrepresented in STEM fields in general and in engineering majors in particular. In this Andean country, during the period 2016-2017 only 30% (1 out 3) of those applying for admission into a STEM field[17]

[12] 76% of students are enrolled in a public school, and 90% of students are registered in schools located in urban areas. Source: 2017 Census of Schools, Ministry of Education (MINEDU), http://escale.minedu.gob.pe/resultado_censos.

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

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

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

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

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

were women.[18] Moreover, while roughly just one in five (19%) female college applicants across the country selected engineering majors during this period; close to one in two (46%) male applicants chose an engineering program.

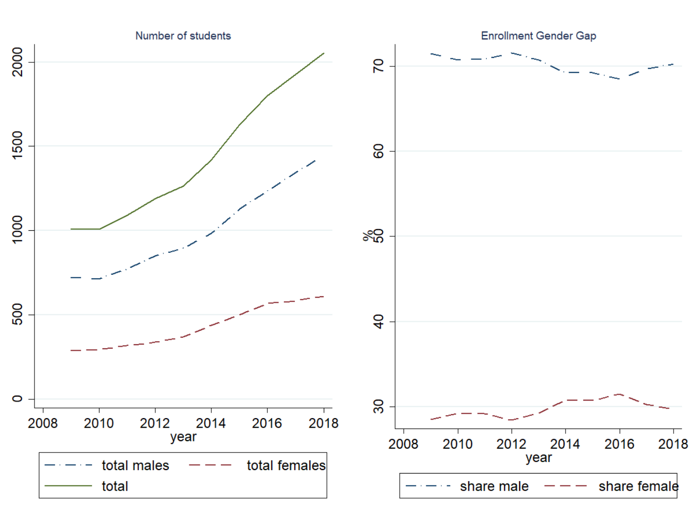
3.2.2 Universidad de Piura

UDEP is a not-for-profit private university located on the city of Piura, in the northern coast of Peru. According to recent national rankings, UDEP is one of the top 10 private universities in Peru, and the top ranked university in the northern region of the country. Historically, UDEP students come predominantly from the Piura region; however UDEP has also consistently attracted students from the neighbouring regions of Lambayeque (to the south) and Tumbes (to the north). Students from these three regions constitute about 95% of the UDEP Piura campus student population. In this sense, UDEP's prestige and reputation as a regional university is mainly concentrated in Piura region and the neighbouring regions of Tumbes and Lambayeque, which we refer to as UDEP's catchment area.

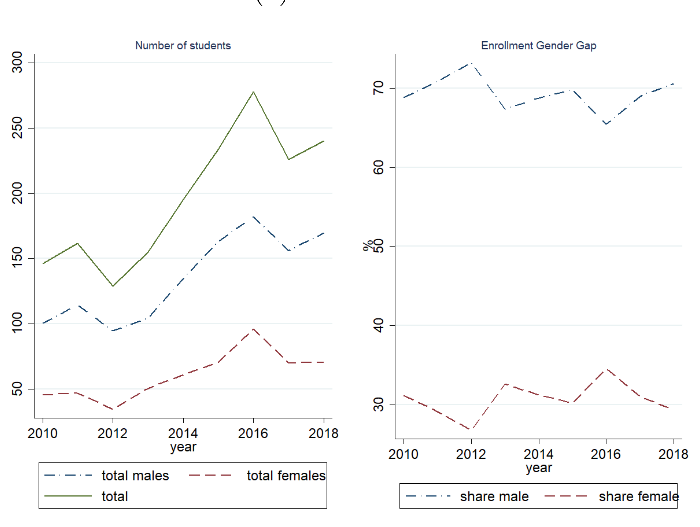
Established in 1969, the UDEP Piura campus has approximately 6,500 undergraduate students across 15 academic programs. Within the category of STEM majors, the Piura campus only offers programs in Engineering.[19] In general, high school students application patterns at UDEP resemble those observed at the country level. According to the university administrative records, only 20% of all female applicants at UDEP selected engineering majors during the period 2016-2017. Moreover, 65% of engineering applicants were male, while just 35% were female.

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

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



(a) All cohorts



(b) First-semester students

Figure 3.1: Enrollment in engineering at UDEP

Notes: Data from administrative records of UDEP.

Figure 3.1, panel (a) depicts the number of students enrolled in engineering at UDEP over the past 10 years. There is clearly an upward trend in engineering enrollment; however, the enrollment gender gap remains steady across all cohorts.[20] As in the rest of the country, males dominate engineering majors at UDEP. There are more than two men for every woman enrolled in engineering at this university.

[20] The pattern is similar if we only consider freshman students (Figure 3.1, panel (b)).

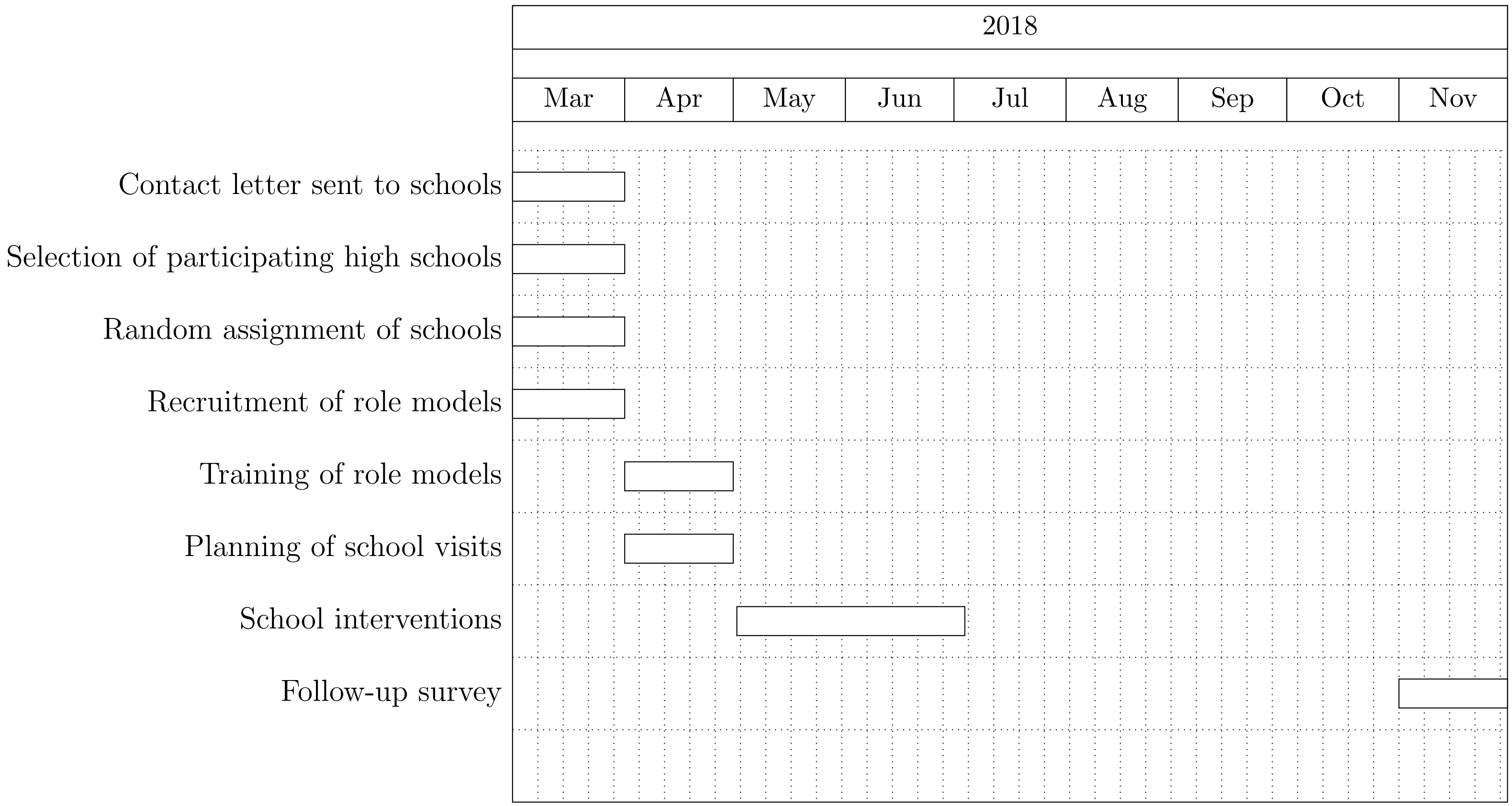
3.2.3 The field experiment

Our experiment started in early 2018 (see Figure 3.2) and targeted female and male senior-year high school students in six Northern Peruvian regions. The school-based interventions consisted of talks carried out by senior female engineering students or very recent female college graduates in engineering from UDEP. The role models talks were delivered during schools visits from May till July 2018.

Content of the interventions. The talks lasted approximately 20-minutes. During their presentations, role models used a set of slides highlighting the following facts: (i) gender differences in brain structure playing no role in determining males' and females' aptitude to pursue engineering majors, (ii) the relevant contributions of female engineers throughout the introduction of successful women in engineering, (iii) definition of engineering as the art of solving problems and as a channel to change the world and make it better, (iv) statements aimed at deconstructing stereotypical views about engineering under the title "Beliefs or Reality?", (v) the experience of the role models at UDEP, and (vi) the relevance of creativity and ingenuity in engineering majors and the capability of girls to become engineers.[21] During and after their presentations, role models answered questions from students.

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

Figure 3.2: Program evaluation timeline



Experimental design and randomization. The experiment was carried out in 18 cities[22] with a total high school, gender balanced population of 225,000 students in 880 schools.[23] Our team had access to a list of 150 schools within this area which have been frequently visited by UDEP admission officials in the last five years to promote UDEP majors and admission mechanisms. We finally chose 109 schools to conform our experimental sample,[24] which overall includes 5,378 students in the 11th grade.[25]

The randomization was stratified at the city level. Half of the schools in each city (or half rounded up or down to the nearest integer where there was an odd number of schools) were assigned to the treatment group whereas the other half were assigned to the control one. In total 51 and 58 schools were randomly assigned to treatment and control, respectively. Table 3.1 shows the baseline characteristics of students and schools by experimental group. As we can observe, our randomization was successful at achieving balance across control and treatment units observable characteristics.

The intervention. Role models visits took place between May and July 2018 and only targeted senior-year high school students. Our role models major in either i) civil engineering, or ii) industrial and systems engineering, or iii) mechanical and electrical engineering. They were 20 to 24 years old, and they were either engineering students in their fourth/fifth year of undergraduate studies or very recent graduates. On average, a treated school was visited by a single role model.[26]

It is worth mentioning that the role models prepared the presentation materials by themselves during several team-work sessions. They agreed on a general template, but adjustments were

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

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

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

[25] Power test calculations where performed by the research team in March 2018. Based on a sample size of 5,450 students (109 clusters and 50 number of subjects per cluster), and an intraclass correlation of 0.05 with power of 80% we are able to detect an MDE of 0.19 standard deviations (with respect to the control group).

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

Table 3.1: Treatment-control balance

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

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

made to capture each role model's own experience as an engineering major. Role models also participated in a feedback session with UDEP faculty members before giving their talks. Most of the role models had previous experience in social events, group projects, and as volunteers in non-profit organizations. Hence, it is safe to say that they have leadership abilities and they were expected to perform relatively well as role models in their field of study.

Role models directly coordinated with UDEP Admissions Office on the date and time of the visits. The Admissions Office provided them with the school visits calendar and role models indicated the name of the person in charge of each talk. A lottery was used by the role models to assign the school visits conditional on each of them delivering approximately the same amount of talks within and outside the Piura region. However, adjustments had to be made depending on role models' availability. On average, each role model delivered 5 talks.[27] Role models also received a monetary compensation, which was solely a function of the visited schools geographical distance relative to the city of Piura, and completely unrelated to performance in any sense. On average each role model received US$ 230 for their participation in the intervention.

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

3.3 Data and empirical strategy

3.3.1 Data

Student follow-up survey. In November 2018, four to six months after the role models' talks were delivered, we conducted a follow-up survey in 101 out of the 109 schools included in the experimental sample.[28] Students' responses to the survey were anonymous. Since we did not

[27] The minimum number of talks performed by a role model was 3 and at the maximum was 7.

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

have access to the students' names or IDs, we are unable to match the survey data with UDEP's admissions or the Ministry of Education's administrative records.[29]

The survey first asked students for their GPA scores in math, language and science in the academic year that preceded our intervention; that is, when they were in 10th grade. We then asked students about the college major they would like to pursue, as well as several questions intended to measure self-confidence, gender beliefs, biases and perceptions. Regarding self-confidence, we asked students if they felt they have the abilities and skills needed to major in engineering at college. With respect to beliefs, biases and perceptions, we first asked students to imagine that they have two friends: "Javier", a boy; and "Lorena", a girl; and that both of them have a school GPA of 20 (the maximum possible score) in math and science. We then asked them which college major they would recommend to "Javier" and to "Lorena".[30] In a similar fashion, we introduced to the students a hypothetical successful individual currently working in the engineering sector, and asked them whether that person was more likely to be a woman or a man. We also asked students to list at most five different engineering fields and collected information on students' expectations of the average monthly salary of a recent college graduate in engineering.

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

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

[30] This question was designed to explore gender bias in STEM conditional on the same math and science skills. See for instance [20].

Data analysis

Balance in observable individual and school level characteristics. We collected information on 5,378 senior-year high school students; 56% (2,998) of them are female and 50% (2,704) are in the treatment group. In Table 3.1 Panel A, we present the balance tests for the combined sample of boys and girls. As we can see, average differences in observable characteristics between treatment and control individuals are relatively small and not statistically significant.[31] Note that the self-reported 10th grade GPA in all subjects, which we will use to measure pre-treatment academic aptitude, is very close among treatment and control students. It can be pointed out that the treatment may have influenced students incentives to either reveal or conceal their 10th grade GPAs in the follow-up survey; so the fact that almost no differences are observed alleviates such concerns. Regarding other individual characteristics, on average students are 16 years old, have 2 siblings, their parents have 13 years of education and in 85% of the cases own their houses. About 95% of students have a working father and 68% have a working mother; while 15% and 3% have an engineer father and an engineer mother, respectively.

Panel B in Table 3.1 compares the school level average characteristics across treatment and control groups. Similar to the individual level case, treated and control schools are relatively similar on average. It is important to highlight that treated and control schools had almost the same performance in the 2015 national standardized evaluation for 8th graders; which corresponds to the year in which students in our cohort were evaluated. Overall, Panels A and B confirm that treated and control students attended similar schools and are of similar academic quality. The results also support the use of self-reported GPAs as a reliable measure of students pre-treatment academic aptitude.

Gender differences in preferences, perceptions, beliefs and stereotypes. In this subsection we exclusively focus on individuals within the control group to asses gender differences in terms of preferences, self-confidence, perceptions, beliefs and stereotypes. As it is shown in Table 3.2, while

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

approximately 40% of boys in the control group preferred an engineering major, only 14% of girls in the control group stated the same preference. The gap remains more or less the same if we only focus on students in the top 10th grade math GPA quartile. In this case, more than 50% of boys stated engineering as their preferred college major, while just 20% of females did so (see Figure 3.3). The observed gap is likely connected to the fact that girls are less confident than boys in their skills and capabilities to pursue a career in engineering, (37% versus 59%), as it can be observed in Table 3.2.

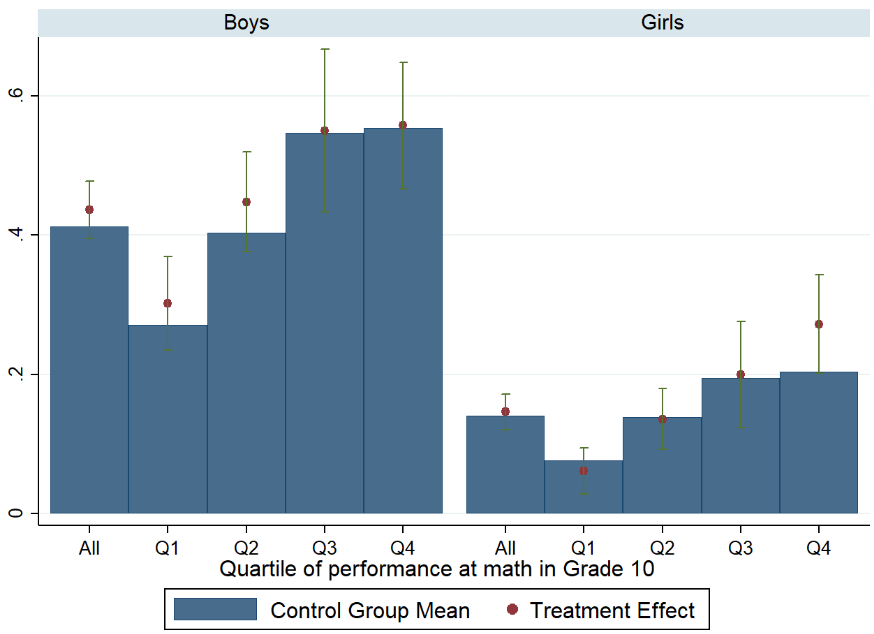
Table 3.2: Difference in preferences for engineering and perceptions: by gender

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

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

Regarding beliefs, biases and perceptions: both boys and girls are more likely to consider a successful professional engineer to be a male. The percentage is nevertheless higher for boys (88% for boys and 61% for girls). Interestingly, nearly half of boys and girls (52% and 49% respectively) suggested engineering as a college major to "Lorena": a hypothetical female high school friend with the highest possible math and science GPA scores. Among girls in the top quartile of the math GPA distribution, this percentage is 58%, which is in clear contrast to the low proportion of them that prefer engineering majors. This suggests that while high math ability girls are likely to project another high math ability girl into an engineer career, they are less likely to do the same for themselves.[32] These findings strongly point to the relevance of interventions that can boost self-confidence among female students, particularly high math ability ones, to pursue engineering majors, such as the role models that we discuss in this paper.

Figure 3.3: Senior-year high school students- preference for engineering by student gender and quartile of baseline math score



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

3.3.2 Empirical strategy

We estimate the following Linear Probability Model (LPM):

$$Outcome_{isc} = \beta_0 + \beta_1 T_{isc} + \beta_2 female + \beta_3 female * T_{isc} + \beta_4 X_{isc} + \theta_c + \varepsilon_{isc} \tag{3.1}$$

[32]Note also in Table 3.2 that students, both male and female, on average are able to list 4 types of engineering majors.

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

The estimate on T_{isc} captures the Intent-to-Treat (ITT) effect of our intervention, since compliance with the initial random assignment was not perfect.[33] To deal with the non-compliance, we also estimate the local average treatment effect (LATE) using random assignment as an instrument for actual treatment. The LATE estimates are very close to the ITT ones and are shown in the Appendix, Table A16.

A possible concern is that treated students may have talked about the role models talks contents with peers in control schools (i.e. friends in the neighborhood who attend a different school, or siblings attending different schools), which we expect to happen with low probability since the school or even the class is the unit within most peer interactions take place [11]. Nevertheless, if spillovers do exist, our estimates could be interpreted as a lower bound of the actual impact of the intervention on students' career preferences.

3.4 Results

This section discusses the intervention's impacts on our main outcomes of interest: i) students' preferences for engineering, ii) student's self-confidence, self-perception and gender stereotypes, and iii) students' preferences for other STEM and non-STEM majors.

[33] Close to 12% of the schools assigned to the treatment group could not be visited by the role models. Non-compliance was mostly related to schools administrators not allowing the visit to take place as well as last minute cancellations due to other school activities taking place.

3.4.1 Effects on preferences for engineering majors

Table 3.3 presents the ITT intervention effect on students' preferences for engineering majors following the specification in equation (3.1). The first column shows the effect on students' preferences without controlling for covariates. Control variables are added gradually in columns 2 to 6. Notice that controlling for covariates does not significantly change either the sign or the size of the estimates. For the overall sample, the intervention does not have a statistically significant impact on boys' and girls' preferences for engineering programs.[34]

Regarding other covariates included in columns 2 to 6 in Table 3.3, several patterns are worth mentioning (See Table A15 in the Appendix). Firstly, in Peru engineering is clearly a male domain, and girls are 26 percentage points less likely to prefer engineering majors than boys (significant at 1%). Within-household peer effects are also likely to be present. Students with female siblings who are engineering students are 6 percentage points more likely to prefer engineering majors (significant at 5%). Similarly, those with a father engineer are 4 percentage points more like to state such preferences. Wealth also plays a role, and students who own their houses are more likely to prefer engineering majors by 3 percentage points. Finally, our results also point to comparative advantage in skills as a factor that is stronly related to preferences for majors. An additional point in grade 10th math GPA is related, *ceteris paribus*, to a 5 percentage points (significant at 1%) increase in the likelihood of preferring an engineering major. Similarly, an additional point in Language (Spanish) 10th grade GPA relates to a 2 percentage points (significant at 1%) decrease in the likelihood of preferring engineering as a major of study.

[34] Also, Figure A11 in the Appendix shows the intent to treat estimates and the effect of other covariates on senior-year students' major preferences, while Figure A12 in the Appendix reports the ITT estimates and the effect of other covariates on students' perceptions.

Table 3.3: The effect of exposure to role models on students' preference for engineering

Dep. Variable:	Prefer Engineering					
Sample:	Full	Full	Full	Full	Full	Full
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.036	0.036	0.035	0.034	0.016	0.018
	(0.025)	(0.026)	(0.026)	(0.024)	(0.024)	(0.024)
Female	-0.263***	-0.265***	-0.266***	-0.265***	-0.258***	-0.261***
	(0.018)	(0.018)	(0.018)	(0.017)	(0.019)	(0.018)
Interaction	-0.023	-0.024	-0.024	-0.024	-0.008	-0.008
(Treatment*female)	(0.027)	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
ITT female:	0.013	0.011	0.011	0.010	0.008	0.010
Treatment + Interaction						
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes
Number of observations (N)	5156	4872	4856	4783	4639	4580
Adjusted R^2	0.105	0.107	0.109	0.114	0.158	0.161
Mean Dv	0.14	0.14	0.14	0.14	0.14	0.14
(Treatment==0)						

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering for the full sample of students who answered the survey. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Given the recent findings in the role models and STEM career choices literature,[35] next we explore if our intervention had heterogeneous effects for different ranges of the students' math ability distribution, as measured by their self-reported grade 10th math GPA. Then we look for local role model effects. That is, if role models effects are stronger among students who reside closer to UDEP historical area of influence.

Heterogeneous effects as a function of math ability. To shed light on how our role models intervention might have impacted students differently depending on their math aptitude, we split the sample into four groups or quartiles as a function of their math GPA in the school year preceding the intervention (10th grade).[36]

[35] Several papers have explored heterogeneous effects of exposure to role models on educational outcomes such as [83], [93], [71], [108], and [29].

[36] These four groups or quartiles are constructed based on the students self-reported 10th grade math GPA. Considering a 20-point grading scale, students in the fourth, highest, quartile have a baseline math GPA in 10th grade higher than 16, those in the third quartile have baseline math scores of 16, those in the second lowest quartile have baseline math scores of 14 or 15, and finally those in the first, lowest, quartile report baseline math scores less than or equal to 13. Moreover, since baseline

Figure 3.3 shows the proportion of senior-year high school students who listed engineering as their most preferred college major, separately by gender and over the quartiles of pre-treatment math GPA. As we can observe, students in the top math GPA quartiles find engineering majors more attractive. We can also observe that our intervention seems to have a positive impact only on girls in the top quartile of the math GPA distribution. For this particular subgroup, the probability of preferring engineering as a college major increases by 7.3 percentage points (significant at 10%) if their school was assigned to the role model intervention. To put this in perspective: this result represents a 36 percent increase from the 20 percent baseline level and conveys a 18.6 percent reduction in the gender gap. There is no evidence in Figure 3.3 of any intervention effect among boys in the upper math GPA quartiles. Note that these boys are already strongly committed to engineering majors: more than 50% of them indicated preferences for an engineering field. In social and cultural contexts in which high math ability boys are already committed to pursuing an engineering major, a soft role model intervention that mainly targets females is unlikely to have an impact on their preferences.

Table 3.4 further explores the ITT intervention effects for the sub-sample of students in the upper quartile of baseline GPA math scores. As we can observe, in all model specifications the ITT estimated coefficients for females in the top math quartile are positive and statistically significant at the 5% level; while the estimated ITT coefficients among boys are very close to zero and not statistically significant. Note however that the coefficients for the interaction term among treatment and female status are not statistically significant (except for column 4 at the 10% level); so we cannot reject the null hypothesis of no different ITT effects across genders.

self-reported GPA math scores are discrete, the quartiles constructed do not have similar sizes: 32% of the observations lay in the first or lowest quartile, 34% of the observations lay in the second quartile, 14% of the observations lay in the third quartile, and 20% of the observations lay in the upper or top quartile.

Table 3.4: The effect of exposure to role models on students' preference for engineering (high ability students)

Dep. Variable:	Prefer Engineering					
Sample:	4th Q math (1)	4th Q math (2)	4th Q math (3)	4th Q math (4)	4th Q math (5)	4th Q math (6)
Treatment	-0.003	0.005	0.001	-0.004	-0.006	-0.002
	(0.043)	(0.047)	(0.047)	(0.046)	(0.049)	(0.049)
Female	-0.335***	-0.338***	-0.338***	-0.331***	-0.309***	-0.307***
	(0.031)	(0.031)	(0.031)	(0.030)	(0.037)	(0.038)
Interaction	0.083	0.082	0.083	0.091*	0.096	0.093
(Treatment*female)	(0.055)	(0.054)	(0.054)	(0.054)	(0.059)	(0.059)
ITT female: Treatment + Interaction	0.080**	0.087**	0.084**	0.088**	0.090**	0.091**
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes
Number of observations (N)	1014	960	957	945	942	939
Adjusted R^2	0.117	0.126	0.128	0.126	0.133	0.136
Mean Dv (Treatment==0)	0.20	0.20	0.20	0.20	0.20	0.20

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering for high ability students (fourth quartile of baseline math scores) , who answered the survey. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

While Figure 3.3 clearly indicates that boys in the upper math quartiles are not affected by the intervention; there seems to be a positive, although not statistically significant, effect among boys in the lower quartiles. To explore this further, the estimations in Table 3.5 focus on boys in the two lowest math GPA quartiles. While the ITT estimates are always positive, in general they are not statistically significant; with the exception of those corresponding to the specifications in columns II and III in Panel B (which focus on the second lowest GPA math quartile).

Heterogeneous effects as a function of geographical location. During their talks, role models clearly stated their UDEP connection. In this sense, they may have been more effective (i.e. better at capturing the student attention) in schools within areas in which our partner university has a relatively high reputation and/or recognition. In fact, UDEP is recognized as the most prestigious

Table 3.5: The effect of exposure to role models on students' preference for engineering (low ability students)

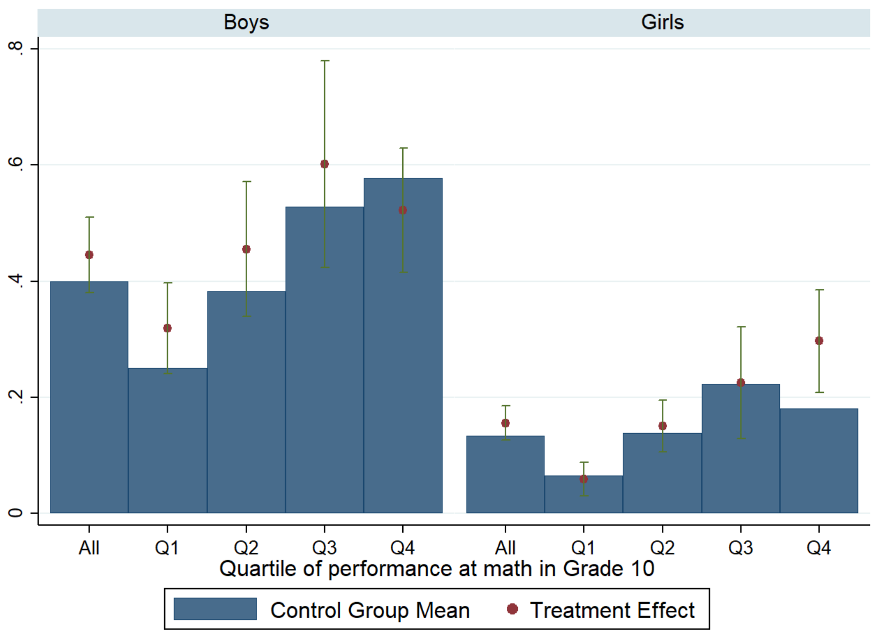
Dep. Variable:	Prefer Engineering					
Panel A:	1st Q math (1)	1st Q math (2)	1st Q math (3)	1st Q math (4)	1st Q math (5)	1st Q math (6)
Treatment	0.0323	0.0309	0.0330	0.0390	0.0224	0.0196
	(0.0333)	(0.0369)	(0.0368)	(0.0354)	(0.0350)	(0.0355)
Female	-0.190***	-0.194***	-0.193***	-0.201***	-0.192***	-0.195***
	(0.0243)	(0.0269)	(0.0268)	(0.0254)	(0.0247)	(0.0251)
Interaction	-0.0478	-0.0504	-0.0545	-0.0543	-0.0389	-0.0387
	(0.0379)	(0.0413)	(0.0410)	(0.0398)	(0.0397)	(0.0398)
ITT female: Treatment + Interaction	-0.016	-0.020	-0.021	-0.015	-0.017	-0.019
Number of observations (N)	1,606	1,504	1,498	1,472	1,462	1,437
Adjusted R^2	0.086	0.086	0.088	0.104	0.117	0.118
Mean Dv (Treatment==0)	0.08	0.08	0.08	0.08	0.08	0.08
Panel B:	2nd Q math (1)	2nd Q math (2)	2nd Q math (3)	2nd Q math (4)	2nd Q math (5)	2nd Q math (6)
Treatment	0.0621	0.0761*	0.0733*	0.0683	0.0624	0.0665
	(0.0435)	(0.0437)	(0.0437)	(0.0427)	(0.0429)	(0.0418)
female	-0.258***	-0.254***	-0.256***	-0.257***	-0.246***	-0.254***
	(0.0359)	(0.0355)	(0.0357)	(0.0354)	(0.0353)	(0.0360)
Interaction	-0.0531	-0.0666	-0.0638	-0.0642	-0.0685	-0.0655
(Treatment*female)	(0.0477)	(0.0472)	(0.0475)	(0.0470)	(0.0475)	(0.0478)
ITT female: Treatment + Interaction	0.00896	0.00945	0.00944	0.00409	-0.00615	0.00109
Number of observations (N)	1,690	1,613	1,609	1,591	1,582	1,558
Adjusted R^2	0.114	0.115	0.116	0.124	0.138	0.146
Mean Dv (Treatment==0)	0.14	0.14	0.14	0.14	0.14	0.14
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences. Sample is restricted to low ability students in the first or second quartile of baseline math scores, who answered the survey. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

university in the Piura region, and this influence and prestige also extends to the neighboring regions of Tumbes (to the North) and Lambayeque (to the South). This is confirmed by the fact that in the last 5 years, 80% to 85% of incoming UDEP's students are from Piura, and close to 95% are from the three above-mentioned regions. On the other hand, the regions of La Libertad, Cajamarca, and Ancash, which are geographically distant from Piura, have their own established local and regional universities.[37]

In Figure 3.4 we restrict our sample to schools within the Piura region and observe that the ITT effect for girls in the top math quartile becomes stronger (15.7 percentage points) and highly statistically significant at the 1% level.

Figure 3.4: Senior-year high school students- preference for engineering by student gender and quartile of baseline math score: only Piura



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

Taking this evidence into account, in Table 3.6 we explore the ITT intervention effects among high-ability students in schools located in Piura only, while in Table 3.7 we perform a similar analysis adding the neighbouring regions of Tumbes and Lambayeque. Our findings indicate that our intervention seems to have been more effective at steering high math skilled girls (upper quartile)

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

towards engineering fields in schools located geographically close to UDEP. Treated girls in the top math GPA quartile and enrolled in Piura schools are 14.1 percentage points more likely to prefer engineering (78% increase from a baseline of 18%) than similar girls in the control group [See Table 3.6, column 1]. Note that the estimate size remains relatively stable after the inclusion of different covariates and that the interaction coefficient term between the treatment and female indicators is always statistically significant at the 1% level. Hence, for the Piura region sample, we can clearly reject the null hypothesis of no difference in treatment effects between boys and girls. When we constrain the sample to the three main regions in terms of UDEP influence (Piura, Lambayeque and Tumbes) in Table 3.7, the ITT estimates for females are slightly smaller that those in Table 3.6, but remain statistically significant at the 1% level.

Table 3.6: The effect of exposure to role models on students' preference for engineering for high ability students in Piura schools

Dep. Variable:	**Prefer Engineering**					
Sample:	4th Q math	4th Q math	4th Q math	4th Q math	4th Q math	4th Q math
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.036	-0.030	-0.037	-0.031	-0.026	-0.012
	(0.056)	(0.058)	(0.056)	(0.057)	(0.059)	(0.057)
Female	-0.360***	-0.362***	-0.361***	-0.352***	-0.316***	-0.296***
	(0.045)	(0.045)	(0.043)	(0.042)	(0.048)	(0.048)
Interaction	0.177**	0.179**	0.177***	0.176**	0.171**	0.153**
(Treatment*female)	(0.069)	(0.068)	(0.064)	(0.067)	(0.070)	(0.071)
ITT female: Treatment + Interaction	0.141***	0.148***	0.140***	0.145***	0.144***	0.141***
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes
Number of observations (N)	549	516	514	511	510	507
Adjusted R^2	0.123	0.136	0.144	0.132	0.133	0.143
Mean Dv (Treatment==0)	0.18	0.18	0.18	0.18	0.18	0.18

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to high ability students (fourth quartile of baseline math scores) in schools located in Piura, who answered the survey. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 3.7: The effect of exposure to role models on students' preference for engineering for high ability students in Piura/Lambayeque/Tumbes schools

Dep. Variable:	**Prefer Engineering**					
Sample:	4th Q math	4th Q math	4th Q math	4th Q math	4th Q math	4th Q math
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.041	-0.039	-0.042	-0.039	-0.049	-0.043
	(0.049)	(0.049)	(0.049)	(0.049)	(0.051)	(0.050)
Female	-0.374***	-0.373***	-0.371***	-0.370***	-0.358***	-0.354***
	(0.032)	(0.033)	(0.032)	(0.033)	(0.039)	(0.042)
Interaction	0.163***	0.162***	0.162***	0.169***	0.179***	0.174***
(Treatment*female)	(0.058)	(0.057)	(0.056)	(0.058)	(0.064)	(0.065)
ITT female: Treatment + Interaction	0.122***	0.124***	0.120***	0.129***	0.130***	0.131***
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes
Number of observations (N)	744	706	704	697	694	691
Adjusted R^2	0.135	0.140	0.141	0.133	0.134	0.141
Mean Dv (Treatment==0)	0.17	0.17	0.17	0.17	0.17	0.17

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences for engineering. The sample is restricted to high ability students (fourth quartile of baseline math scores) in schools located in Piura/Lambayeque/Tumbes, who answered the survey. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In Table 3.8 and Table 3.9, we explore the ITT effects among students in the two lowest math quartiles, first for the Piura region only and then for the Piura, Lambayeque and Tumbes regions altogether. As in Table 3.5, the ITT among boys is always positive (between 6 and 9 percentage points) but statistically significant, generally at the 10% level, only in some specifications. Note that the estimated effect for girls in this case is very close to zero and not statistically significant. Since role models emphasized that a person does not have to be a math genius to major in engineering, and that skills like imagination and creativity are also important to pursue engineering careers, it seems possible that some low math ability boys may have adjusted their engineering preferences as a result of this specific message. Nevertheless, given the weak nature of the evidence in this case, we believe these results should be treated with caution.

Table 3.8: The effect of exposure to role models on students' preference for engineering (low ability students) in Piura schools

Dep. Variable:			**Prefer Engineering**			
Panel A:	1st Q math (1)	1st Q math (2)	1st Q math (3)	1st Q math (4)	1st Q math (5)	1st Q math (6)
Treatment	0.070	0.068	0.066	0.073*	0.058	0.051
	(0.042)	(0.047)	(0.046)	(0.043)	(0.044)	(0.044)
Female	-0.181***	-0.184***	-0.186***	-0.199***	-0.194***	-0.198***
	(0.033)	(0.038)	(0.037)	(0.034)	(0.035)	(0.034)
Interaction	-0.076	-0.080	-0.082	-0.078	-0.058	-0.053
(Treatment*female)	(0.048)	(0.053)	(0.052)	(0.050)	(0.051)	(0.050)
ITT female: Treatment + Interaction	-0.006	-0.012	-0.016	-0.005	0.000	-0.002
Number of observations (N)	1033	964	960	943	937	919
Adjusted R^2	0.099	0.104	0.108	0.129	0.138	0.136
Mean Dv (Treatment==0)	0.06	0.06	0.06	0.06	0.06	0.06
Panel B:	2nd Q math (1)	2nd Q math (2)	2nd Q math (3)	2nd Q math (4)	2nd Q math (5)	2nd Q math (6)
Treatment	0.0824	0.0986*	0.0957	0.0837	0.0893	0.0932*
	(0.0591)	(0.0589)	(0.0585)	(0.0562)	(0.0579)	(0.0555)
female	-0.238***	-0.225***	-0.229***	-0.234***	-0.212***	-0.220***
	(0.0499)	(0.0500)	(0.0497)	(0.0481)	(0.0493)	(0.0503)
Interaction	-0.0620	-0.0723	-0.0679	-0.0645	-0.0824	-0.0826
(Treatment*female)	(0.0612)	(0.0607)	(0.0604)	(0.0586)	(0.0597)	(0.0610)
ITT female: Treatment + Interaction	0.0204	0.0263	0.0278	0.0192	0.00695	0.0106
Number of observations (N)	1,128	1,073	1,070	1,055	1,051	1,031
Adjusted R^2	0.103	0.099	0.100	0.109	0.132	0.144
Mean Dv (Treatment==0)	0.14	0.14	0.14	0.14	0.14	0.14
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences. Sample is restricted to low ability students (first or second quartile of baseline math scores) in schools located in Piura, who answered the survey. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 3.9: The effect of exposure to role models on students' preference for engineering (low ability students) in Piura/Lambayeque/Tumbes schools

Dep. Variable:	Prefer Engineering					
Panel A:	1st Q math (1)	1st Q math (2)	1st Q math (3)	1st Q math (4)	1st Q math (5)	1st Q math (6)
Treatment	0.066*	0.062	0.064*	0.077**	0.064*	0.059
	(0.035)	(0.038)	(0.038)	(0.036)	(0.036)	(0.036)
Female	-0.178***	-0.186***	-0.186***	-0.194***	-0.184***	-0.187***
	(0.025)	(0.028)	(0.028)	(0.026)	(0.025)	(0.025)
Interaction	-0.078*	-0.079*	-0.083*	-0.085**	-0.073*	-0.070*
(Treatment*female)	(0.041)	(0.043)	(0.043)	(0.042)	(0.042)	(0.041)
ITT female: Treatment + Interaction	-0.012	-0.017	-0.019	-0.008	-0.009	-0.012
Number of observations (N)	1265	1183	1178	1158	1151	1132
Adjusted R^2	0.097	0.103	0.106	0.124	0.131	0.131
Mean Dv (Treatment==0)	0.07	0.07	0.07	0.07	0.07	0.07
Panel B:	2nd Q math (1)	2nd Q math (2)	2nd Q math (3)	2nd Q math (4)	2nd Q math (5)	2nd Q math (6)
Treatment	0.058	0.071	0.068	0.060	0.059	0.064
	(0.052)	(0.051)	(0.051)	(0.049)	(0.050)	(0.048)
female	-0.248***	-0.241***	-0.242***	-0.245***	-0.233***	-0.239***
	(0.042)	(0.041)	(0.041)	(0.041)	(0.040)	(0.041)
Interaction	-0.041	-0.048	-0.045	-0.043	-0.054	-0.053
(Treatment*female)	(0.055)	(0.053)	(0.054)	(0.053)	(0.053)	(0.054)
ITT female: Treatment + Interaction	0.0168	0.0227	0.0230	0.0172	0.00557	0.0114
Number of observations (N)	1,357	1,294	1,291	1,274	1,266	1,246
Adjusted R^2	0.098	0.094	0.095	0.106	0.123	0.135
Mean Dv (Treatment==0)	0.14	0.14	0.14	0.14	0.14	0.14
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Parent engineer	No	Yes	Yes	Yes	Yes	Yes
Own house	No	No	Yes	Yes	Yes	Yes
Parent education FE	No	No	No	Yes	Yes	Yes
Baseline scores in 10th grade	No	No	No	No	Yes	Yes
Student's age (in years)	No	No	No	No	No	Yes
Has female sibling engineer	No	No	No	No	No	Yes

Notes: This table reports the intent to treat (ITT) estimates on students' career preferences. Sample is restricted to low ability students (first or second quartile of baseline math scores) in schools located in Piura/Lambayeque/Tumbes, who answered the survey. Column 1 reports the ITT estimates without covariates. Covariates are included from column 2 to column 6. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 3.10 summarizes the ITT estimates for our role model interventions separately by gender, geographical location and 10th grade math GPA quartile. In Panel A of Table 3.10, the ITT estimates correspond to the full sample, while in panel B we restrict the analysis to schools in the region of Piura and adjacent regions of Tumbes and Lambayeque. Overall, our intervention increased the likelihood that a female senior-year high school student in the upper math quartile who resides geographically close to UDEP, stated engineering as her most preferred major. No effects for female students in the 1st, 2nd, and 3rd quartile were found in any specification.[38] Moreover, we also find some, although week, evidence suggesting that female role models may have also affected the engineering major preferences of low math ability male students.

Table 3.10: The effect of exposure to role models on students' preference for engineering by quartile of math performance

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

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for engineering, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

3.4.2 Self-confidence, gender beliefs, biases and stereotypes

To shed light on the mechanisms behind our intervention, in the follow-up survey we presented students with several statements intended to measure self-confidence and gender stereotypes. We begin this analysis with Table 3.11, which focuses on students' self-confidence in their own skills and aptitude to pursue engineering majors. We observe that treated girls in the top quartile of the math score distribution are 12.5 percentage points (significant at 5%) more likely to indicate that they do have the necessary skills and aptitude to major in engineering. This specific result suggests that role models were a source of inspiration, positively influencing these girls' self-confidence, which, as shown before, resulted in an increased preference for studying engineering.

Interestingly, Table 3.11 also shows that high math ability treated boys appear to be less confident

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

Table 3.11: The effect of exposure to role models on students' perceptions by quartile of math performance: self-confidence

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

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' self-confidence in their aptitude and skills to pursue an engineering major, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

in their aptitude and skills to pursue an engineering major. As pointed before, one of the key pieces of information in the role models talks was that you don't need to be a mathematical genius to major in engineering, and that other skills, such as imagination and ingenuity, are also relevant. This message may have influenced the perceptions of these boys about the role of math skills alone to succeed in engineering majors. Note however that the adjustment in perceptions did not affect their stated preferences. In a social context in which high math ability boys are expected to be engineers, this extra piece of information and the subsequent adjustment in perceptions, is likely not to be adequate to fully switch them out of engineering majors. In any case, such issues should be kept in mind when designing similar role model interventions. Also interestingly, in the case of boys in the two lowest math ability quartiles, the results in Table 3.11 suggest a 4 to 5 percentage points increase in the self-confidence outcome; however, it is not statistically significant. Once again, the key message on aptitudes other than math ability to succeed as an engineer may be playing a role in this case. Overall, boys within the UDEP's catchment area seem to have been carefully listening to the information provided in the talks.

In Tables 3.12 and 3.13, we evaluate whether or not the role models affected gender beliefs, biases and stereotypes. In our follow-up survey, we described a person who happens to be a successful engineer and asked students whether they thought that this person was more likely to be male or female. We constructed an indicator that took the value of one when the student responded that the person was more likely to be male, and zero otherwise. Table 3.12 presents the results related to this question. In general, the coefficients for all females quartiles have the expected sign: treated girls are less likely to indicate that the successful engineer is male, but the estimated coefficients are relatively small and not statistically significant. The estimated coefficients for boys are also negative, but smaller in absolute size than the female ones and not statically significant. We speculate that a lasting impact on gender beliefs, biases and stereotypes, possibly needs a longer than 20 minutes intervention in countries like Peru.

Also regarding gender stereotypes, we presented students in our sample with two hypothetical high school students: a female named "Lorena" and a male named "Javier", and describe both as high math and high science ability individuals. We then asked students to suggest a major to each of them. The outcome variable takes the value of one if the student recommended an engineering major to "Lorena". The results in Table 3.13 indicate that treated girls were not more likely than control ones to recommend engineering majors to "Lorena". It is nevertheless important to note that close to 60% of top math ability girls in the control group are already recommending engineering to the hypothetical high math ability girl; but very few are applying this recommendation to themselves. In other words, self-confidence seems to be the critical issue; and as we have shown before, it is self-confidence what is primarily being impacted by our role models. In the case of treated boys, Table 3.13 indicates that those in the second-lowest quartile residing within UDEP catchment area were more likely to suggest an engineering major to our hypothetical female student. As mentioned before, the fact that role models strongly emphasized that women can also succeed as engineers may be the driving factor behind the boys results. Clearly boys seem to have been paying attention to the information delivered.

Table 3.12: The effect of exposure to role models on students' perceptions by quartile of math performance: success exclusively for men in the sector

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

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' perceptions of males successfulness in engineering, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 3.13: The effect of exposure to role models on students' perceptions by quartile of math performance: gender stereotypes

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

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' recommending engineering to Lorena (hypothetical female friend), separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Although the role models did not provide either any information about earnings associated with engineering careers (as they wanted it to be about abilities) or an exhaustive list of engineering specializations, in the follow-up we asked students related questions as we wanted to see if this intervention made them seek out more information on engineering majors. In this case, we find some statistically significant effects for girls in the top math quartile and boys in the second lowest math quartile; however, the size of the effects is relatively small. As we can see in Tables 3.14 and 3.15, treated high math ability girls listed 0.2 less engineering fields than those in the control group (who listed 4.7); while the salary expectations of boys in the second lowest math quartile increased just by 1% relative to the control group.

Table 3.14: The effect of exposure to role models on students' perceptions by quartile of math performance: knowledge of engineering fields

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

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' number of engineering fields listed, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 3.15: The effect of exposure to role models on students' perceptions by quartile of math performance: earnings expectations

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

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on students' knowledge about earnings associated with engineering careers, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

3.4.3 Are treated students more likely to prefer the role models' engineering majors?

Our role models were from one of the following three engineering majors: industrial, civil and mechanical-electrical, which are actually the only three engineering specializations offered at UDEP. During their presentations, the role models emphasized their own major as well as their connection with UDEP. Given this context, role models may have been more effective at promoting their own engineering major or UDEP engineering majors in general.[39] To test for this possibility, we create a binary outcome variable which equals one if the student stated as her/his preferred engineering major to be any of the role models' ones and zero otherwise. As shown in Panel A in Table 3.16, girls in the top math ability quartile are 10.4 percentage points (significant at 5%) more likely to list one of the role models' engineering majors. Within UDEP's catchment area, the likelihood of preferring these three engineering majors increased by 13.4 percentage points (significant at 1%)

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

for high-ability girls, as shown in Panel B of the same table. Note also that there is no statistically significant effect among boys, and the estimated coefficients in this case are relatively small. These results suggest that treated female students are clearly connected with the specific experience of their role models, and confirm that role models were a source of inspiration. The results also provide important lessons for the design of role model interventions. STEM role models seem to be more effective at influencing career paths that are closely related to their own experiences.

Table 3.16: Students' preference for the role models' majors by quartile of math performance

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

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for the role models' majors offered at UDEP (industrial engineering, civil engineering, or mechanical engineering), separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**}\, p < 0.05,^{*}\, p < 0.1$.

3.4.4 More on local effects: school distance to UDEP

In this section we provide additional evidence on whether students in schools located geographically close to UDEP were more likely to be encouraged to pursue engineering fields by our role models, but also on whether or not the effects in UDEP proximate schools are different from those in far-away ones. Using longitude and latitude coordinates, we calculate the distance in kilometers from the schools in our sample to UDEP. Using the estimated distances, Tables A19-A24 in the Appendix show that geographical closeness matters. Girls in the top GPA math quartile are 17.2 percentage points (significant at 1%) more likely to prefer engineering after a role model exposure if they come from a school located below the median distance (less than 43 km) from UDEP (Column 6, Table A19). Moreover, the effect for schools above the median distance is close to zero and we can reject the null hypothesis of equal ITT effects among nearby and far-away schools. The analysis for boys in the bottom quartiles of math scores is presented in Table A20 and leads to similar conclusions.[40] Overall, these results confirm that the relevance of UDEP's role models is higher in the geographical areas where UDEP historically has had a stronger influence.

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

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

As we can observe in Table 3.17, the intervention clearly affected the preferences for non-STEM majors among high math aptitude girls. Treated girls in the top math quartile are less likely to report that they will choose a non-STEM major. Also note that the absolute value of the estimated coefficients are relatively similar to those observed for high math aptitude girls in Table 3.10. This clearly indicates that our intervention is shifting the preferences of high math aptitude girls from non-stem majors to engineering ones. There is also some, though weaker, evidence in this table suggesting that the intervention is doing the same for boys in the lowest math ability quartiles within UDEP's catchment area. In a similar fashion, we also investigate if students in our intervention were more likely to prefer STEM fields other than engineering (i.e. Life-Science, Mathematics, Statistics, Physics) as a consequence of being exposed to a young engineer role model. We do not find neither sizable nor statistically significant estimates in this case. This quite likely due to the extremely low share of students who prefer STEM majors different from engineering in Peru.[41]

[40] In Tables A21-A24 we evaluate the effect on different subgroups of individuals based on location and math skills. The results seem to be robust for different subgroups of students. The liking for engineering increases after the intervention in nearby schools.

[41] These results are available upon request.

Table 3.17: The effect of exposure to role models on students' preference for non-stem fields by quartile of math performance

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

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for non-STEM fields, separately by quartile of performance in math and for i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

3.5 Robustness checks

3.5.1 Alternative measures of ability: Science and math

In our baseline estimations, we explored differential ITT effects as a function of students' math ability only, which is generally regarded an indicator of students' capacity to major in engineering. In this section, in addition to math scores, we also consider 10th grade science scores, as competence in science may also be an indicator of the student aptitude to major in engineering. We therefore construct a binary indicator equal to one if the student ranked in the top quartile in both math and science, and zero, otherwise. As expected, the ITT effect in this case is positive and statistically significant for female students in the top, math and science, quartile and who reside within UDEP's catchment area (See Appendix Table A17). These girls are 21 percentage points (significant at 1%) more likely to prefer engineering as a result of our role models intervention.

3.5.2 ECE math scores

While our balance tests confirm that treatment and control schools are of similar academic quality, the fact that we are not using standardized scores to define our math ability quartiles may be a cause of concern for some readers. In order to alleviate these concerns, we again estimate the specifications in Table 3.7 using the school average math section performance in the *Evaluación Censal de Estudiantes* (ECE), which is a standardized national examination administered annually to 8th graders, as a comtrol variable. As students in our sample were in the 8th grade in 2015, the 2015 ECE results allow us to control for the academic quality of our school cohorts. The estimations results are shown in Table A18 in the Appendix. As it can be observed, the results are very similar to those in Table 3.7.

3.6 Conclusion

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

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

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

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

4

To Quit or to Stay? Academic Probation in College

4.1 Introduction

As individuals get more education they are more likely to achieve better labor outcomes and opportunities in the future. Despite the advantages of human capital accumulation and in particular college education, college drop-out rates have been increased. For instance, in the United States, the overall dropout rate for undergraduate college students is 40%.[1] Increasing enrollment in Higher Education is one element of governments' human capital accumulation agenda. Consequently, there are many studies looking at possible determinants of college drop-out rates and policies to motivate students to continue undergraduate studies. However, less attention has been given to the academic programs students enroll in and whether being well matched to an academic program benefits students in the middle and short term. A well-functioning market would be one in which students attend the institution and academic program offering the highest net marginal benefit conditional on their characteristics.

[1] Source: Hanson, Melanie. "College Dropout Rates" EducationData.org, November 22, 2021, https://educationdata.org/college-dropout-rates.

Testing the consequences of mismatch is an empirical challenge due to the correlation between motivation and cognitive abilities and university choices. On one hand, students who are talented and motivated are more likely to remain at college and complete their studies. On the other hand, students who manage to graduate are more likely to be talented in their fields of study. Moreover, more motivated students may make "better" choices regarding which university and program to enroll in. Few studies have used methods to overcome these issues, but the evidence does seem to point to the finding that mismatch is relevant for student outcomes.

Early studies have looked at the effects of mismatches on students outcomes. In particular, the match literature studies how the selection of college changes according to the ability of the student. For instance, [52] evaluates the effect of college quality and fit on degree completion and labor outcomes. The authors find that higher attaining students benefit more from college quality in terms of the time it takes to complete their degree; and that a good student-college match increases labor outcomes. Most of the previous published work focuses on the US context, and to the best of my knowledge there are not non-US published studies. This research chapter adds to the mismatch literature by analyzing educational mismatches in a developing country. Given that the fit between student ability and selection of academic programs or college seems to matter, questions looking to identify the types of students that are more likely to be impacted by mismatches are of great interest to education economists. With respect to this question, several studies have investigated the type of students who mismatch in the US by mainly comparing student ability to college quality to determine the mismatch.[2] This paper goes further than simply examining match at the university level, by providing match measures at the university major level. In addition, it is outside the US based and uses a university policy related to academic probation rules.

In the particular context of educational policies to increase the fit of students to college programs, researchers in the field have analyzed the effect of policies on students' outcomes but the majority of them have primarily focused on positive incentives.[3] Only a handful of papers examine the

[2] See for instance: [51], [121], [23].

[3] See for instance [9], [92]. These studies look at the effect of financial rewards and academic support services on motivation and academic performance.

effects of college remediation [21], [79], academic probation [96], [61], and negative incentives in general in a postsecondary setting. Among the few studies looking at academic probation in college all of them evaluate the effect of this university procedure on students' academic performance and drop-out rates in developed countries; with consequences probable very different to what would have happened in a developing country where strong gender stereotypes, lack of self-confidence, and high college attrition rates are predominant. Furthermore, the cost of opportunity to attend college is high which can make students more responsive to signals of ability and bad grades at the start of their program.[4] This paper uses longitudinal data from one campus at a private Peruvian university to evaluate the effect of one university policy- academic probation in a regression discontinuity framework.[5] Understanding the reaction of students towards signals of academic performance is very important to design the most effective educational policies to allocate students to careers more suitable for them.[6]

This paper also contributes to the growing literature on gender differences in response to signals of ability and educational incentives. Previous studies have found that women are more susceptible and responsive to negative shocks in grades and positive incentives than men [9], [53], and the size of this effect can be even larger in societies with gendered patterns and low levels of self-confidence of women.

The empirical strategy of this study (RD design) is motivated by the idea that students with a GPA just above the academic probation cutoff provides a good control group for those students with a GPA just below the academic probation cutoff. The identification strategy of the effect of

[4] For example, [96] examine the causal effect of academic probation on students' subsequent academic performance and drop-out rates using a quasi experimental technique (regression discontinuity design), and a single Canadian university. A more recent study, [61], evaluates academic probation in the United States Higher Education System looking at four universities located in Texas.

[5] Academic probation is a tool used by most universities to ensure students achieve minimum academic requirements. In general the status of the student depends on the student's Grade Point Average (GPA)- if the student's GPA is below a certain threshold for a fixed number of semesters, then the student is placed on academic probation. Analogously, students are considered in good standing if they have met the minimum performance criteria judged by the GPA. Academic probation serves as a warning or wake-up call to students that they might need to improve academically, otherwise, they may face penalties; their future enrollment status and graduation from the university might be compromised.

[6] On one hand, university rules regarding academic performance of students are essential to guarantee high quality of graduates and a good reputation of the institution/college. However, university rules based on probationary status could be pervasive if they demotivate students who are good but their sensitivity towards bad grades makes them withdraw the program without trying hard.

academic probation on students' outcomes relies on the assumption that other characteristics of the students are continuous through the cutoff and that there is no manipulation of GPA exerted by students or instructors.

The results suggest that exposure to academic probation increases the probability to drop-out the subsequent semester from the program and it also has negative and significant effects on female students' subsequent GPA for those women who stay. Interestingly, differences in the size of the RD coefficient are found based on academic program; STEM versus non-STEM fields of study. Students in STEM fields such as engineering are more affected by academic probation than students in non-STEM fields, and they have higher probability to drop out due to bad performance. The estimates of the policy on drop-out rates are statistically significant mainly for men. I attribute these findings to gender stereotypes predominant in STEM fields where men are expected to enroll in male-dominated careers and to perform well in them.

4.2 Institutional Context

The main data comes from administrative records of an elite private university in Peru[7] and contains students' information such as their current GPA, academic program, academic semester, date of entrance and admission to the university, graduation status and students' ability at the baseline measured by the students' math and verbal performance in "*Prueba de Aptitud Escolar*" (PAE) administered by the university every year.[8] The supply of academic programs offered by the university is described in Table A26 in the Appendix, and the administrative records available for this study correspond only to students enrolled in engineering, business administration, economics, architecture, and accounting majors.

When a student is placed on academic probation, a communication is sent to the student notifying

[7] The university is a private university in Peru. It ranks among the nine top universities in Peru according to the QS Latin American University Rankings 2020. It is considered a medium size university with around 8000 students and 6 faculties.

[8] The PAE exam is a high school aptitude test administered to senior high school students who want to apply to the university. The test is administered in approximately 150 schools in Northern Peru included Lima, Cusco, and Arequipa. It measures knowledge of math and verbal subjects acquired during high school years, topics that students admitted are supposed to know for an undergraduate formation. The PAE test is a standardized test with two sections one for verbal and one for math, centered at 500 points with a standard deviation of 100. A critical feature of the test is that students are required to state their most preferred academic program prior to taking the test, although this stated preference is not binding.

them of their current academic standing and the reason why they are on probation. Students who have been placed on probation and who fail to improve in their grades are suspended after subsequent sessions. In general one of the reasons why students are classified on probation is to have a GPA less or equal to 8 out of 20.[9] Students on probation can avoid suspension and return to good academic standing status by bringing their GPA up to the threshold of 8. Students who fail to improve their GPA the subsequent semester following probation are suspended for one year. If suspended students choose to return to the university and again they do not manage to rise their grades and to obtain a GPA above 8 they must leave the university without any option to return to the same academic program (i.e. permanent suspension).

In general students with a GPA below or equal to 8 for two consecutive semesters or three non-consecutive semesters are suspended for one year. In case the student decides to return and continues with a GPA below or equal to 8, the second suspension is permanent.[10]

4.3 Theoretical Context

Consider a model with different types of students based on their ability level. In particular, student i is a low type or a high type, $i \in \{l, h\}$, and needs to decide whether to continue in the program or to drop, and the effort levels. The students do not know their true ability. Indeed they might form mistaken beliefs about their own ability at the start of the program by being either over-confident or under-confident.

Let's say the true ability of student i is $\theta_i = \hat{\theta}_i + \varepsilon_i$. Where ε_i represents the self-perception error, and $\hat{\theta}_i$ is the self-perceived ability. The students overestimate their ability if $\varepsilon_i < 0$ and they underestimate if $\varepsilon_i > 0$. The realization of the error term depends on "k", which is the cutoff above which students avoid a probationary status.[11]

[9] The grade system in Peru is a 0-20 scale, with 11 being the lowest passing grade. Students receive an academic warning (probationary status) in the following cases: i) Fail a course twice, ii) Being reincorporated to the university after a temporal suspension, iii) To have a GPA less than or equal to the minimum required of 8.

[10] At the end of the semester, students can receive a disciplinary sanction based on their performance, and they should leave permanently or temporarily the university. For example, the reasons why students should temporarily leave the university are: i) Fail a course for the third time, ii) Obtain a GPA equal or less than eight for two consecutive semesters or three non-sequential semesters.

[11] The error term is distributed as a normal random variable: $\varepsilon \sim N(\mu, \sigma^2)$.

Students receive a signal of ability in the current period, $t = 1$, and update beliefs hold at $t = 0$ following the realization of the signal. The signal is a deterministic function of "k". If they passed the cutoff ($\varepsilon > 0$) the signal is good news, and if they remained below the cutoff ($\varepsilon < 0$) the signal is bad news. A student's prior belief is denoted by $p(\lambda)$, and it represents the prior belief that students have of the event $GPA_i > k$. The fraction of individuals that decides to quit college depends on the student's type given by the event, and the individual's utility. Formally, students maximize their expected utility given their beliefs by choosing effort level and whether to drop-out or not from the program:

$$_{\{e_i\}}\mathcal{L} = \sum_{\theta_i \in \Theta} \lambda(\theta_i | signal_i) U_i(\theta_i, signal_i, e_i)$$

Students decide how much effort to exert the next subsequent academic period, and then they choose whether to continue or drop. The student's utility is a function of the academic performance net of effort cost. The academic performance of the students is increasing in effort and ability, and the cost of effort is inversely proportional to ability. The intuition behind the last statement is that effort is more costly for low ability than high ability types.

Individuals maximize:

$$EU_i = Expected\_score - Expected\_Cost\_of\_effort$$

$$EU_i = p(\hat{\lambda}_i)\left\{[e_i\theta_i] - \frac{ce_i^2}{\theta_i}\right\}$$

$$\frac{\partial EU_i}{\partial e_i} = p(\hat{\lambda}_i)\left\{\theta_i - \frac{2ce_i}{\theta_i}\right\}$$

$$e_i^* = \frac{\theta_i^2}{2c}$$

Under the assumption that the posterior belief is informative and $p(\hat{\lambda}_i) \neq 0$, the individual exerts effort e_i^*. $p(\hat{\lambda}_i)$ is the posterior belief of having a GPA above the minimum of k. Intuitively, effort decreases when marginal cost (c) increases. In addition, e_i^* increases with ability but at a decreasing rate. The student's utility is calculated by replacing the optimal effort level e_i^* into the utility functional form.

$$U_i^* = \frac{\theta_i^3[p(\hat{\lambda}_i)]}{4c} > 0$$

Students whose outside option value is greater than U_i^* drop, the outside option is the utility the student gets if he works full-time instead of going to college. Notice that the student's utility is directly affected by the probability of not receiving a probationary status. A higher probability for good performance increases the student's utility and reduces the probability of drop-out, ceteris paribus. Furthermore, the utility is positively affected by student's ability but at a decreasing rate. High ability students prefer to stay in college rather than to quit, and utility is inversely correlated with the effort cost. Individuals with high effort cost have less incentive to stay in college. In order to guarantee the participation constraint, the outside option has a value of zero, $\theta_i \neq 0$, and $p(\hat{\lambda}_i) \neq 0$.

4.3.1 The simple case of two effort types

For simplicity, let's assume there are two effort levels: i) High effort e_h which is costly, ii) Low effort e_l which has a cost of zero. For a certain $\theta_i = \theta_0$, the student with ability θ_0 exerts high effort iff:

$$e_h\theta_0 - \frac{ce_h^2}{\theta_0} \geq e_l\theta_0$$

$$\theta_0^2(e_h - e_l) \geq ce_h^2$$

$$\theta_0 \geq e_h\sqrt{\frac{c}{e_h - e_l}}$$

The student exerts low effort iff

$$\theta_0 \leq e_h \sqrt{\frac{c}{e_h - e_l}}$$

Without loss of generality, under two student types: i) Low type (θ_l), ii) High type (θ_h).

- High ability type exerts high effort iff $\theta_h \geq e_h \sqrt{\frac{c}{e_h - e_l}}$
- Low ability type exerts high effort iff $\theta_l \geq e_h \sqrt{\frac{c}{e_h - e_l}}$

Students put high effort if they expect a higher academic performance by exerting high effort ($\Delta e = e_h - e_l$ is large), the cost of high effort is low, and they are confident to avoid academic warnings with non-zero probability.

The Separating Equilibrium: Each type takes a different action. Hence, the equilibrium outcome reveals the type of the student. The conditions for this equilibrium are:

$$\theta_h \geq e_h \sqrt{\frac{c}{e_h - e_l}} > \theta_l$$

High type will exert high effort and low type will exert low effort.

Because $\theta_h > \theta_l$, there are three equilibrium scenarios:

Case 1: $\theta_h > \theta_l \geq e_h \sqrt{\frac{c}{e_h - e_l}}$. Both types of students exert high effort

Case 2: $\theta_h \geq e_h \sqrt{\frac{c}{e_h - e_l}} > \theta_l$. High ability type exerts high effort and low ability type exerts low effort.

Case 3: $e_h \sqrt{\frac{c}{e_h - e_l}} > \theta_h > \theta_l$. Both types of students exert low effort.

The game and the Equilibrium: In the previous results I assumed that the students do not know their type, and students' utility does not depend on other players action. In this section, I introduce a signaling model with two players and the instructor. Consider there is asymmetric information and the student has perfect information about his type $\theta \in [0,1]$. The game proceeds as follows: 1) The Nature moves and decides the student type, 2) Assume the student is already enrolled in college, and chooses the units of effort, 3) The instructor observes the student's effort and forms an estimate of ability θ given the academic performance of the student and effort choice. The student receives a payoff based on this estimate.[12] The strategies of the individuals are set such that the high types do not exert less effort than the low types. If the low types weakly prefer to exert high effort, the high types strictly prefer it. This sort of results follows from the assumption that it is less costly to exert effort for high types compared to low types.

Suppose a reward schedule exists and it is a function of effort exerted by the student, $W(e)$. $e(\theta_i)$ is type i optimal choice of effort. $e(\theta)$ is the maximum optimal choice of effort given by:

$$e(\theta) = \{argmax[W(e) - C(\theta, e)]\}$$

Following [65], assume two reward levels W_L^* and W_H^*. A partially separated equilibrium is given by the threshold $e^* > 0$ and $\theta^* \in (0,1)$ such that:

$$W(e) = \begin{cases} W_H^* & if \quad e \geq e^* \\ W_L^* & if \quad e < e^* \end{cases}$$

$$e(\theta) = \begin{cases} 0 & if \quad \theta < \theta^* \\ e^* & if \quad \theta \geq \theta^* \end{cases}$$

Where the payoffs W_L^*, W_H^* could be interpreted as the return to effort for low and high ability students, respectively. In the equilibrium, student's reward should be equal to the student's ability

[12] In reality, effort is not perfectly observed. However, I assume workers work next to employers, and employers monitor what employees are doing at any time.

or productivity. Hence, W_L^* is the average ability of individuals in the interval $[0, \theta^*]$, and W_H^* is the average ability of individuals in the interval $[\theta^*, 1]$ The effort threshold (e^*) is interpreted as equivalent to the minimum effort that is required to avoid the academic probation.[13]

In summary, the model described above could be used to analyze how students might respond to being placed on academic probation. For instance, consider the choice of two students whose GPAs were near the academic probation cutoff, one to the left and the other one to the right. The student just above the cutoff decides among the following alternatives at the start of each period: i) return to the academic program and achieve low GPA, ii) return to the academic program and achieve high GPA, iii) drop-out of the program. In contrast, the student just below the cutoff has a different set of options: i) return to the academic program but with the pressure to exert high effort (achieve high GPA), ii) drop-out of the program.

In the next section, I present the data adjusted to this theoretical framework to investigate the effect of being placed on academic probation on the students' enrollment choices and academic performance.

4.4 Data and Empirical Strategy

4.4.1 Data

The data used in the analysis are from administrative records of college students from a Peruvian university described in section 4.2. Observations are at the student-term-year level and cover a eight-year period from 2010 to 2018 with each academic year broken into three terms (term 1, term 2, and summer term). The data includes student term registration status, academic program, GPA, gender, age, parental education, and a measure of ability in math and language (i.e. Spanish). I perform falsification tests and I use some students' characteristics as controls in some regression specifications. I restrict the sample to students I observe for at least two terms.[14] I also restrict

[13] In this framework and considering an outside option value (O) such that $W_L^* < O < W_H^*$, a student subject to academic probation drops-out of college.

[14] The data contain students through the end of the second term of the 2018 academic year and I restrict the sample to students who entered in the first term of the 2018 academic year or earlier, this allows me to clearly observe the drop-out

Table 4.1: Summary Statistics

	Mean	SD	N	Min	Max
Baseline verbal score PAE	528.87	90.41	556	215.33	865.61
Baseline math score PAE	551.74	93.25	556	335.15	769.29
Admission mechanism was PAE	0.25	0.43	1077	0	1
Number of courses attempted in the first term	5.68	0.83	1412	1	7
Age at entrance (in years)	18.32	1.54	1412	17	23
Male (=1 if male; =0 if female)	0.59	0.49	1412	0	1
Mother education is college	0.38	0.48	953	0	1
High school is private	0.70	0.46	1078	0	1
Preference for engineering at the baseline	0.39	0.49	555	0	1
Preference for management at the baseline	0.49	0.50	555	0	1
Enrolled in management	0.60	0.49	1412	0	1
Enrolled in engineering	0.36	0.48	1412	0	1
Outcomes					
Distance from cutoff in 1st term	2.89	1.65	1412	0	9.05
Distance from cutoff in 2nd term	3.14	1.58	1412	0	9
Distance from cutoff in 3rd term	3.28	1.71	1266	0	12
Distance from cutoff in 4th term	2.90	1.54	1139	0	11
Distance from cutoff in 5th term	3.19	1.64	1024	0	12
Distance from cutoff in 6th term	3.32	1.61	907	0	12
Average distance from cutoff	3.11	1.04	1412	0.16	6.71
Ever on academic probation	0.35	0.48	1412	0	1
On academic probation in the first term	0.12	0.33	1412	0	1
Left university/program after the first AP (GPA<=8)	0.09	0.28	1412	0	1
Average distance from cutoff at next evaluation (GPA)	2.62	1.94	1412	-7.58	7.8
Distance from cutoff at next evaluation (GPA) for 2nd term	2.75	2.18	1412	-7.84	9
Distance from cutoff at next evaluation (GPA) for 3rd term	3.02	2.13	1266	-7.30	12
Ever suspended	0.09	0.29	1412	0	1
Graduated from program	0.43	0.50	909	0	1

Notes: The sample consists on 1412 students and observations are at the student-term-year level.

the sample to students entering the university between the ages of 17 and 23 (97% of the remaining sample). Finally, I limit the sample to students within a close distance to the academic probation cutoff (approximately 2.5 grade points and it corresponds to the largest bandwidth I use in the regressions).[15] The final sample includes 1412 students.[16]

Table 4.1 shows the descriptive statistics for the final sample of 1412 students and 3018 observations. The students average entry age in their selected program is 18.3 years. The sample is composed of 59% male students and each student on average took 5.7 courses in the first term. A

condition of the student and subsequent academic performance, the two main outcomes in this study. In addition, I restrict the analysis to students who were enrolled in only one program at most to avoid switch major cases.

[15] I also evaluate the effect of the academic probation policy on students' outcomes using different bandwidths, including the optimal bandwidth of [36]. The choice of the degree of the polynomial and bandwidth size involves a trade-off between bias and efficiency. According to [90], high order polynomials and narrow bandwidths reduce the bias but at the cost of greater asymptotic variance. It is recommended to use at most a second order polynomial since estimates make become misleading when the polynomial order is higher than two [see for instance, [66]].

[16] Further restricting the sample by eliminating from the sample periods when students have to drop-out due to i) temporal or permanent suspension, ii) keeping only periods up to the first academic probation term or no probation in case it applies reduce the sample to 1390 students.

large sample of students face academic probation at least once during enrollment in their program (35%). Similarly, 12% of the students are placed on academic probation after their first semester.

Among the outcomes under analysis for this study are drop-out rates of the academic program. 9% of the students left the program after the first signal of probation determined by a GPA of less than or equal to 8. It seems that students fail to meet the university' academic requirements and that might have an effect on the students' decision to drop-out as well as on the students' effort and GPA improvement following probation. I exploit variation around the minimum GPA of 8 to evaluate the causal effect of academic probation on students' effort, academic performance, graduation and drop-out rates.

4.4.2 Empirical Strategy

This study evaluates the effect of being placed on academic probation taking into account i) all the periods the student is enrolled in a specific academic program (i.e. panel data structure), ii) the first term only, iii) the first year only, iv) up to the third term. At the end of each term the probation status for student i is a deterministic function of his GPA:

$$PROB_i^t = 1(GPANORM_i^t < 0) \tag{4.1}$$

Where $GPANORM_i^t$ is the distance between the student i's term GPA and the probationary threshold given by the university policy. The discontinuity in probation condition is a deterministic function of the student's GPA, therefore, I use a "sharp" regression discontinuity design to estimate the causal effect of the policy on students' education outcomes.

Similarly avoiding academic probation can be denoted as follows:

$$T_i^t = 1(GPANORM_i^t > 0) \tag{4.2}$$

The identification strategy relies on the assumption that other students characteristics related to the outcomes are continuous throughout the probationary threshold. If this is true, then the treatment effect of the policy for students near the probationary threshold can be obtained by comparing the outcomes of the students just below the probationary threshold to those just above the probationary threshold.

I estimate the following equation:

$$Y_i^t = \alpha_0 + \alpha_1 PROB_i^t + h(GPANORM_i^t) + X_i'\alpha_2 + \varepsilon_i \tag{4.3}$$

Where Y_i^t is an outcome for student i at semester t (term t), $h(GPANORM_i^t)$ is a continuous function of students' standardized term GPAs and it represents the distance from the probationary cutoff in absolute value, $PROB_i^t$ is an indicator equal to one if the student's GPA is below the probationary cutoff, X_i is the matrix of control variables, and ε_i is a random error term. The coefficient of interest is α_1, and it is the estimated impact of being placed on academic probation. I perform separate RD regressions for each term with a particular interest for the first term at the university as it gives the effect of academic probation on students outcomes for freshman students who have just started their program and might not be able to manipulate their grades. Also, freshman students might not be very familiar with the policy or affected by past experiences and interactions with peers.

4.4.3 Validity of the RD Design

I use the discontinuity around the probationary academic cutoff to identify the effect of academic probation on students' drop-out rates and subsequent academic performance. The key identifying assumption of the RD design is that the assignment of students is as good as random around the boundary. One potential concern is that the term GPA of the student is manipulated. This could appear if students just below the cutoff were influencing their GPAs to avoid probation, for example, by talking with instructors to ask for higher grades to raise their GPA above the cutoff point. However, the manipulation of GPA is very unlikely since GPA is calculated as a weighted average of final course grades in the term, and different instructors teach different courses per term at the university. Nevertheless, to mitigate these concerns I conduct a formal validity check following [99]. [99] tests the null hypothesis of continuity of the density of the running variable, which is the distance from the probationary GPA. The test is implemented by running kernel local linear regressions of the log of the density separately on both sides of the probationary cutoff. Figure A13, in the Appendix, shows the distribution of students' term GPA relative to the campus cutoff, with bin size of 0.04 grade points and a bandwidth of less than 1. The estimated discontinuity at the probationary cutoff is not statistically significant at 5%, which indicates that the distribution of students is continuous through the threshold.[17] Moreover, Table A27 shows the results of the manipulation test implemented with the *rddensity* command on *Stata* and using kernel local quadratic regressions. All the p-values for the different subgroups and bandwidths are greater than 5%. Thus, I fail to reject the null hypothesis of no manipulation of the running variable.

The research design requires both observable and unobservable characteristics that are related to the students outcomes to be continuous at the probationary cutoff. Figure A14 and Figure A15 explore the continuity of observable covariates through the probationary cutoff. Any significant discontinuity would indicate that students with specific features are more likely to manipulate their term GPA and to avoid being placed on probation. Overall, I do not find significant jumps in students' baseline scores measured by the PAE test, number of courses attempted in the first term at the university, mother education, high school type, age at entry, and gender.

I also examine the validity of the RD design by checking whether some students' characteristics are smoothly distributed around the boundary. I implement RD regressions by using the predetermined students' characteristics as dependent variables:

$$X_i = \pi_0 + \pi_1 PROB_i^t + g(GPANORM_i^t) + \omega_i \tag{4.4}$$

Where g(.) is a polynomial function that changes on each side of the probationary cutoff and ω_i is the error term. Table 4.2 presents the covariate balance tests. The sample includes college

[17] I have also verified that there are not significant discontinuities in the distributions of students for each subgroup used in my analysis.

students' administrative records within a narrow distance from the probationary cutoff given by the university policy. I use a bandwidth of 2.5 grade points on each side of the cutoff. In the first two columns of Table 4.2, I report the descriptive statistics on students' characteristics for those on no probation and probation, respectively; and using the panel structure of the data first. In the last two columns, I present the coefficients on the dummy variable T_i under a linear and quadratic triangular kernel specification. Based on the results, all the covariates except the baseline score in language (Spanish) are balanced. However, the difference in baseline language scores between those students under probation and no probation is only marginal significant at 10% level.[18]

Table 4.2: Covariate balance tests: All term-year for students

Variables	No Probation	Probation	Adjusted Difference	
			Linear	Quadratic
	(1)	(2)	(3)	(4)
Student and Household Controls				
Math score PAE	556.620	520.324	24.727	30.075
	(91.411)	(88.456)	(15.897)	(24.029)
Verbal score PAE	530.303	501.079	25.677*	39.564*
	(91.728)	(87.301)	(15.183)	(22.666)
Male	0.594	0.644	0.023	0.016
	(0.491)	(0.479)	(0.051)	(0.077)
Age at entrance	18.324	18.385	-0.054	-0.192
	(1.554)	(1.558)	(0.180)	(0.277)
Mother education is college	0.374	0.332	0.053	0.049
	(0.484)	(0.471)	(0.063)	(0.096)
School is private	0.715	0.725	0.001	-0.070
	(0.452)	(0.447)	(0.054)	(0.080)
Total courses at first term	5.647	5.589	0.015	-0.021
	(0.789)	(0.885)	(0.095)	(0.143)
Observations	2543	475		

The distance (in grade points) from the probationary cutoff is used to determine academic probation status. The discontinuity estimates in columns (3) and (4) are adjusted for a linear and a quadratic polynomial, respectively, in grades points from the probationary cutoff. Standard deviations are reported in parentheses in columns (1) and (2). Standard errors are reported in parentheses in columns (3) and (4). ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

[18]The results are robust to alternative uniform and epanechnikov kernel functions. Also they are similar if I cluster robust standard errors at the program level.

4.5 Results

4.5.1 Main Results

I estimate equation (4.3) using the so called restricted sample throughout the study and it includes observations with students normalized term GPA between -2.5 and 2.5. I use a quadratic polynomial function of the running variable $GPANORM_i$. Figure 4.1 plots the enrollment decision of the students and subsequent academic performance, the two main outcomes in this study against the grade point distance from the university probationary cutoff. Panel (a) of Figure 4.1 evaluates the effect of academic probation on drop-out decisions from the program while panel (b) evaluates the effect of academic probation on students' effort to improve their GPA. The results show an increase in drop-out rates and a decrease in consecutive period GPA as a consequence of academic probation. The effect of academic probation on drop-out rates could be larger in particular for first semester students who might over react after receiving a signal of their skills and ability to succeed in the program. Moreover, it is less likely for first year students to manipulate their GPA as they are less familiar with the university policy itself. Taking into account these considerations, I replicate a similar analysis and restrict the sample to fewer periods. Panel (a) of Figure 4.2 depicts the RD estimates for the first three terms while panel (b) restricts the estimation to the first term. There is a clear discontinuity of drop-out rates at the cutoff for the subsample in panel (a). On the other hand, the jump in drop-out rates at the cutoff is marginally significant for first term students only. The decrease in the number of observations may explain the weak statistically significant discontinuity in drop-out rates at the probationary cutoff for this subgroup of students.

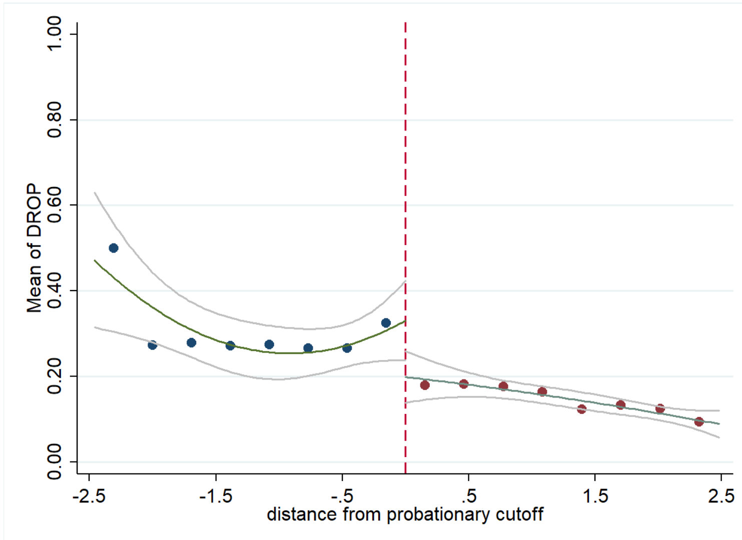
Table 4.3 presents the RD estimates (coefficient of no probation status) on students drop-out rates from their programs and students' subsequent GPA over different subperiods using equation (4.3). Columns (1) and (2) estimate the RD strategy without controls and in the last two columns of the Table, I include additional controls on individual characteristics. Notice that in panel A, which considers all terms, the coefficient on drop-out is negative and statistically significant at 5% while the estimate on next period GPA is positive but insignificant. The estimates remain robust to the inclusion of covariates. Individuals above the probationary threshold exhibit lower probability to quit their studies than those below. In particular, students under probation are 13.5 percentage points more likely to quit their program. Interestingly, the size of the effect on drop-out rates increases up to 33 percentage points (significant at 1% level) when I consider a maximum of three terms of data. (see Panel D). Also, students subject to academic probation at the end of their first term are 16 percentage points more likely to drop-out, and the estimate is marginally significant at 10%. Finally, all the specifications in the Table show academic probation having no effect on students' subsequent GPA. This result can be explained by the timing of the analysis or a combination of opposite responses between men and women.[19]

[19] I expect the effect of the policy on academic performance to be effective only at the start of Higher Education (i.e. first term) rather than halfway or later on because senior students exposed to academic probation might have strong preferences to leave the program temporally or permanently rather than to put effort at increasing their GPA. They may be already tired, demotivated to continue the program. Despite this expectation, the small sample size of first term students makes difficult to detect a sizable and/or significant effect for this sub-sample.

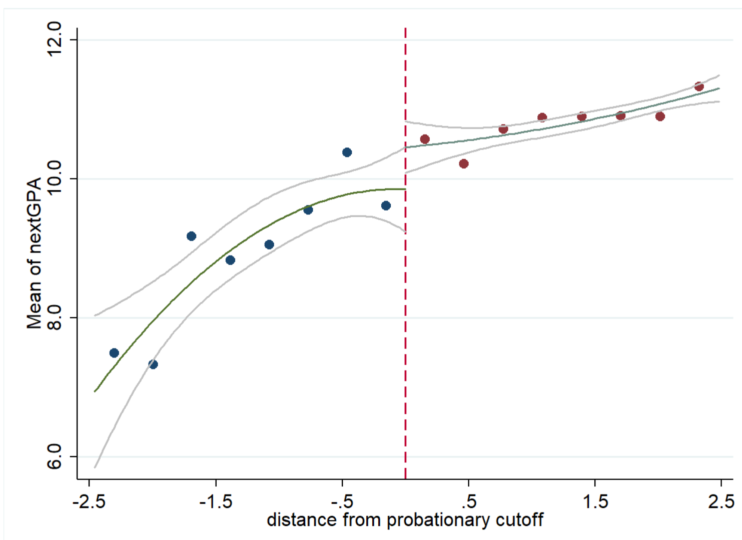
Table 4.3: Regression discontinuity coefficients of no academic probation on enrollment decisions and academic performance

	Dependent Variables			
	DROP	nextGPA	DROP	nextGPA
	(1)	(2)	(3)	(4)
Panel A: All terms				
RD estimate	-0.135**	0.459	-0.130*	0.263
	(0.067)	(0.465)	(0.077)	(0.535)
Controls	No	No	Yes	Yes
Effective Obs.	3018	2733	2010	1824
Panel B: 1st term				
RD estimate	-0.160*	1.239	-0.110	0.512
	(0.088)	(0.876)	(0.101)	(0.954)
Controls	No	No	Yes	Yes
Effective Obs.	617	617	424	424
Panel C: Until the second term				
RD estimate	-0.153	0.755	-0.163	0.349
	(0.101)	(0.807)	(0.115)	(0.993)
Controls	No	No	Yes	Yes
Effective Obs.	1061	988	709	660
Panel D: Until the third term				
RD estimate	-0.330***	0.622	-0.309***	0.374
	(0.096)	(0.742)	(0.105)	(0.901)
Controls	No	No	Yes	Yes
Effective Obs.	1439	1305	934	846

This table reports reduced form RD estimates on enrollment decisions and subsequent academic performance over different sub-periods. All specifications include separate quadratic polynomial functions in the distance from the probationary cutoff. The bandwidth size is 2.5 grade point. Controls include age at entrance (in years), gender, number of courses attempted in the first term at the university, mother education, and high school type. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.



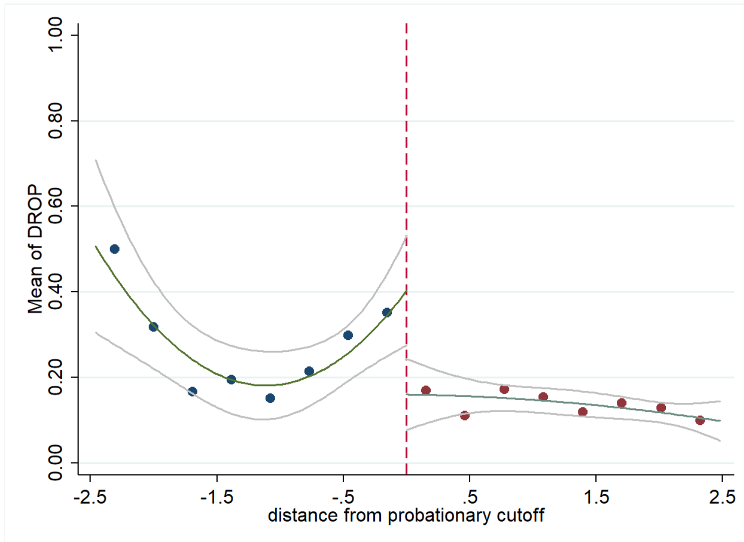
(a) Effect of academic probation on drop-out from program rates



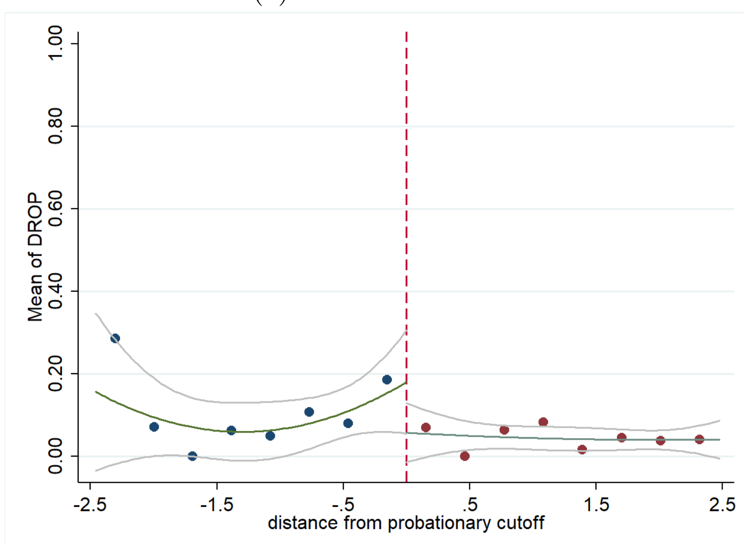
(b) Effect on academic probation on subsequent GPA

Figure 4.1: Drop-out and next GPA by the distance from the probationary cutoff

Notes: The red vertical line in each figure indicates the probationary cutoff, which is used as the university policy and normalized to 0. I use a 2.5 grade point distance GPA bandwidth on each side. The dots represent the average drop-out rates of students from the program (in panel a) and the average subsequent GPA of students (in panel b) within 31.25% of a grade point in the restricted sample. The solid lines are fitted values using quadratic regressions. The gray colored lines are the 95 percent confidence intervals.



(a) Until third term



(b) First term

Figure 4.2: Effect on drop-out: Different periods

Notes: The red vertical line in each figure indicates the probationary cutoff, which is used as the university policy and normalized to 0. I use a 2.5 grade point distance GPA bandwidth on each side. The dots represent the average drop-out rates of students from the program for the first three terms (in panel a) and the first term only (in panel b), and within 31.25% of a grade point in the restricted sample. The solid lines are fitted values using quadratic regressions. The gray colored lines are the 95 percent confidence intervals.

4.6 Robustness Checks

4.6.1 Placebo Tests

The validity of the RD design relies on the smoothness of all predetermined factors besides academic probation at the boundary. In the previous section I confirmed balance of most observable baseline individual characteristics; however, other confounding factors might exist. Thus, I check this possible case and I perform a placebo test by artificially moving the boundary 2.5 points forwards or 2.5 points backwards. The former case considers a probationary cutoff of 10.5 instead of 8 while the latter case uses a cutoff of 5.5. The students are not subject to academic probation on both sides of the placebo boundary with a falsified probationary cutoff of 10.5. Therefore, I expect not to observe a discontinuity change in leaving the program if there are no other confounding factors. Similarly, students are highly exposed to academic probation on both sides of the placebo boundary with a falsified probationary cutoff of 5.5 and because of that I expect not to observe a discontinuity change in students' behavior at the falsified cutoff. Panel A of Table 4.4 presents the results with all the periods I have for each student in the restricted sample, panel B restricts the analysis to first term, panel C up to the second term, and panel D up to the third term. The RD estimates are not statistically significant using alternative boundaries.

Table 4.4: Placebo Test

	Dependent Variables			
	DROP	nextGPA	DROP	nextGPA
	(1)	(2)	(3)	(4)
BW 2.5 points forward				
Panel A: All terms				
RD estimate	-0.016	-0.344***	-0.029	-0.426***
	(0.019)	(0.127)	(0.021)	(0.157)
Controls	No	No	Yes	Yes

Effective Obs.	8122	7620	5435	5183
Panel B: 1st term				
RD estimate	0.021	0.072	-0.010	0.188
	(0.037)	(0.343)	(0.040)	(0.444)
Controls	No	No	Yes	Yes
Effective Obs.	1121	1121	732	732
Panel C: Until the second term				
RD estimate	-0.014	-0.126	-0.018	-0.003
	(0.035)	(0.251)	(0.042)	(0.312)
Controls	No	No	Yes	Yes
Effective Obs.	2215	2150	1469	1424
Panel D: Until the third term				
RD estimate	-0.009	-0.215	-0.024	-0.142
	(0.031)	(0.205)	(0.038)	(0.250)
Controls	No	No	Yes	Yes
Effective Obs.	3179	3066	2100	2028
BW 2.5 points backward				
Panel A: All terms				
RD estimate	-0.016	-0.344***	-0.029	-0.426***
	(0.019)	(0.127)	(0.021)	(0.157)
Controls	No	No	Yes	Yes
Effective Obs.	8122	7620	5435	5183
Panel B: 1st term				
RD estimate	-0.067	-4.081*	-0.191	-3.197
	(0.406)	(2.414)	(0.412)	(2.375)
Controls	No	No	Yes	Yes
Effective Obs.	166	166	122	122

Panel C: Until the second term				
RD estimate	0.083	-3.383	0.156	-2.994
	(0.415)	(2.154)	(0.395)	(1.995)
Controls	No	No	Yes	Yes
Effective Obs.	227	204	156	143
Panel D: Until the third term				
RD estimate	0.283	-3.438*	0.562	-2.972
	(0.389)	(2.011)	(0.393)	(1.955)
Controls	No	No	Yes	Yes
Effective Obs.	296	243	198	165

This table reports RD estimates on enrollment decisions and subsequent academic performance using alternative boundaries. All specifications include separate quadratic polynomial functions in the distance from the boundary. Controls include age at entrance (in years), gender, number of courses attempted in the first term at the university, mother education, and high school type. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

4.7 Heterogeneous effects and possible mechanisms

While the data of this study does not contain neither information on students' beliefs and perceptions about their skills and abilities to succeed in their chosen programs nor variables to measure possible mechanisms at play; my hypothesis is that the university policy for academic probation can somehow influence students' self-confidence and knowledge about their true skills. It also aids to the retention of talented students in their programs improving the student-academic program match.

The extra information received by students classified under probationary condition can indirectly impact students' behavior and increases drop-out from programs. The effects might be significant and stronger in contexts where students are less resilience towards receiving bad grades. In order to investigate different students attitudes while facing academic probation and how these behaviors differ between women and men, and students enrolled in STEM and non-STEM programs; I replicate the main estimation dividing the sample based on gender and academic program. Table 4.5 reports the regression discontinuity estimates of the effects of no academic probation (RD estimate) on the students' decisions to drop-out from their respective programs and subsequent academic performance measured by GPA, separately for women and men. For the subsample of observations up to the third term, the results show that academic probation increases drop-out for men but not for women (see panel D).[20] In addition, while women facing academic probation do not change their enrollment decisions, they tend to perform worse next period after the reception of an academic warning. The contrasting results by gender are consistent with the hypothesis that gender differences regarding self-confidence, resilience, outside opportunities, and perceptions to academically succeed in their field of study can be driven forces behind these results.[21]

Table 4.5: Heterogeneous effects: By gender

	Dependent Variables					
	DROP	nextGPA		DROP	nextGPA	
		All	If DROP=0		All	If DROP=0
	(1)	(2)	(3)	(4)	(5)	(6)
Women						
Panel A: All terms						
RD estimate	-0.160	1.994**	1.984**	-0.168	1.653*	2.146**
	(0.104)	(0.851)	(0.803)	(0.113)	(0.858)	(0.831)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	1202	1099	1014	818	747	701
Panel B: 1st term						

[20] Notice that the RD estimate shown in the table corresponds to the effect of no academic probation on the outcome variable.

[21] [3] also find gendered patterns on drop-out rates. The authors investigate the determinants of dropout rates during college years by using experimental and administrative data. According to their findings, family background and personal characteristics explain dropout rates. Males are more likely to dropout after controlling for family background and personal characteristics, preference, beliefs, and non-cognitive abilities while females remain with the decision they took at the start of college. According to the authors, a reason why females remain with their choice is because they make choices based on more information compared to males. Girls are better informed about labor market earnings. In addition, personality traits, higher ability, having parents with a college degree contribute to less dropouts.

RD estimate	-0.227	4.608***	3.722***	-0.228	2.447	2.689*
	(0.155)	(1.502)	(1.262)	(0.201)	(1.674)	(1.589)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	239	239	224	162	162	150
Panel C: Until the second term						
RD estimate	-0.036	4.489***	4.019***	-0.177	3.062**	3.317**
	(0.164)	(1.317)	(1.078)	(0.149)	(1.366)	(1.455)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	424	391	366	288	264	247
Panel D: Until the third term						
RD estimate	-0.249	3.240**	2.645**	-0.260	2.642**	2.768**
	(0.184)	(1.300)	(1.252)	(0.178)	(1.290)	(1.379)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	574	523	485	377	342	318
Men						
Panel A: All terms						
RD estimate	-0.130	-0.567	-0.400	-0.118	-0.853	-0.671
	(0.090)	(0.545)	(0.592)	(0.109)	(0.649)	(0.664)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	1816	1634	1511	1192	1077	1012
Panel B: 1st term						
RD estimate	-0.130	-0.391	-0.323	-0.065	-0.278	-0.033
	(0.126)	(0.928)	(0.972)	(0.116)	(1.177)	(1.121)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	378	378	358	262	262	253
Panel C: Until the second term						

RD estimate	-0.215*	-1.062	-0.564	-0.197	-1.242	-0.866
	(0.124)	(0.829)	(0.844)	(0.179)	(1.083)	(1.094)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	637	597	560	421	396	380
Panel D: Until the third term						
RD estimate	-0.370***	-0.686	-0.205	-0.351**	-0.755	-0.358
	(0.112)	(0.798)	(0.915)	(1.623)	(1.012)	(1.020)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	865	782	729	557	504	481

This table reports reduced form RD estimates on enrollment decisions and subsequent academic performance over different sub-periods and by gender. All specifications include separate quadratic polynomial functions in the distance from the probationary cutoff. The bandwidth size is 2.5 grade point. Controls include age at entrance (in years), number of courses attempted in the first term at the university, mother education, and high school type. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

The results for first-year students show a significant and positive effect on subsequent GPA for women but not for men. Women not exposed to academic probation in their first term and who stay in their program have 3.7 higher GPA than women exposed to academic probation. This pattern may be an indicator that women are less resilience to bad grades and academic warnings could even demotivate them and make them perform worse in the near future.[22] In contrast, first year male students, who decide to stay after the notification of academic probation, perform better, but the effect is not statistically significant. My results are different from previous studies and predictions of [18]. [18] argue that academic probation leads to an increase in "performance standards", and has both a discouragement effect that increases attrition and an encouragement effect that rises performance of remaining students.[23] There are two possible interpretations of my results. On one hand, my findings that academic probation policies deteriorate academic performance in

[22] I find that the effect of academic probation on subsequent GPA to be particularly larger and statistically significant for women in non-STEM fields.

[23] Other studies on academic probation policies have reported different results than mine on subsequent academic performance. For instance, [61] using data from four Texas Universities found that students placed on academic probation after their first semester had better second semester academic performance but higher rates of leaving the program in subsequent terms.

the short term and increase attrition raise a concern that these policies may be exacerbating the problem of low college completion rates in a developing country like Peru.[24] On the other hand, the university policy may aid to a better allocation of students towards academic programs, in a context where students do not have much information of what career to follow. For example, in Peru every student at high school takes the same subjects part of the curriculum elaborated by the Ministry of Education independent of their preferences for college studies. Under the absence of tracks like science tracks; a university policy that gives students information of their skills early in their college years could reduce educational mismatches with further implications for the whole Economy throughout a raise in aggregate productivity.

Table 4.6 reports the RD estimates by academic program grouped in STEM and non-STEM fields.[25] Overall, for those students in STEM fields, their enrollment decisions are affected by academic probation rules as twice as those students who are enrolled in non-STEM programs. Column 1, Panel D, reports the RD estimates for observations up to the third term. Students avoiding probation in engineering and non-engineering programs, are 54.6 (significant at 1%) and 23 (significant at 5%) percentage points less likely to drop-out, respectively. These results are mainly significant for men. In contexts where male students are expected to perform well; for example in male dominated fields such as engineering, an under-performance of men might have higher effects on male students selection to leave those programs. To further explore this result, I evaluate the effect of academic probation on students' graduation rates from their chosen programs. The negative estimate under the probation indicator confirms that for male students in STEM fields and exposed to academic probation in their first term, drop-out is permanent rather than temporal, and the probability of graduation declines by more than 80 percentage points.[26]

[24] According to statistics of the Ministry of Education, before the COVID-19 pandemic, the rate of interruption of university studies was 12.6%. Among the reasons why students decide to quit their studies are failing a subject, problems with school preparation, financial problems, lack of interest in the major, among others.

[25] For my analysis, I consider engineering as the only STEM field. Business Administration, Economics, Accounting, and Architecture are grouped under the non-STEM category.

[26] The results are available upon request.

Table 4.6: Heterogeneous effects:
Engineering (STEM) versus non-engineering (non-STEM)

	Dependent Variables					
	DROP	nextGPA		DROP	nextGPA	
		All	If DROP=0		All	If DROP=0
	(1)	(2)	(3)	(4)	(5)	(6)
Engineering						
Panel A: All terms						
RD estimate	-0.171	0.964	1.477*	-0.107	1.360	1.523
	(0.133)	(0.709)	(0.776)	(0.165)	(1.002)	(1.065)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	1098	996	909	671	604	559
Panel B: 1st term						
RD estimate	-0.041	2.097	2.253	0.141	2.371	2.544
	(0.231)	(1.338)	(1.418)	(0.111)	(2.737)	(2.918)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	178	178	162	106	106	99
Panel C: Until the second term						
RD estimate	-0.375	0.488	1.638	-0.259	1.263	3.317**
	(0.242)	(1.141)	(1.216)	(0.501)	(2.571)	(1.455)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	326	302	278	187	169	247
Panel D: Until the third term						
RD estimate	-0.546***	1.099	2.154*	-0.621*	3.301	3.435
	(0.203)	(1.056)	(1.197)	(0.342)	(2.251)	(2.293)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	470	430	393	263	237	223

Non-engineering						
Panel A: All terms						
RD estimate	-0.109	0.074	0.040	-0.132	-0.411	-0.030
	(0.083)	(0.624)	(0.644)	(0.088)	(0.674)	(0.694)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	1920	1737	1616	1339	1220	1154
Panel B: 1st term						
RD estimate	-0.185*	0.747	0.505	-0.168*	-0.376	-0.019
	(0.103)	(1.058)	(1.014)	(0.092)	(1.144)	(1.144)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	439	439	420	318	318	304
Panel C: Until the second term						
RD estimate	-0.063	0.635	0.667	-0.133	-0.378	0.154
	(0.117)	(0.980)	(0.976)	(0.118)	(1.145)	(1.190)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	735	686	648	522	491	466
Panel D: Until the third term						
RD estimate	-0.230**	0.279	0.114	-0.221*	-0.591	-0.171
	(0.116)	(0.962)	(1.008)	(1.114)	(1.070)	(1.115)
Controls	No	No	No	Yes	Yes	Yes
Effective Obs.	969	875	821	671	609	576

This table reports reduced form RD estimates on enrollment decisions and subsequent academic performance over different sub-periods and by major. All specifications include separate quadratic polynomial functions in the distance from the probationary cutoff. The bandwidth size is 2.5 grade point. Controls include gender, age at entrance (in years), number of courses attempted in the first term at the university, mother education, and high school type. ***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively.

4.8 Concluding Remarks

This paper adds to the education mismatch literature by studying the student-academic program mismatch in a developing country where strong gender norms are predominant. I assess a university policy linked to academic probation rules to explore the causal effect of the policy on students education outcomes.

Using plausible exogenous variation in academic probation induced by one university policy in Peru, I find that students exposed to academic probation are more likely to drop-out from their programs and female students who remain in their programs following probation perform worse measured by subsequent GPA.

While I do not have data available on students' beliefs and perceptions regarding their majors and suitability for their programs, I discuss some possible mechanisms at play based on differences found of the effects of the university policy by gender and field of study.

I have presented evidence on the negative effect of academic probation on students' semester registration. However, this study in any sense can talk about the underlying welfare effects of dropping-out from academic programs. The decision of dropping out from a program in which the student under-perform may lead to better outcomes in the middle and long-term, which cannot be measured in this study due to data limitation. For future studies in this topic, it would be important to evaluate the causal effects of academic probation on students' labor outcomes and choices after leaving the program as well as welfare effects of academic probationary policies at Higher Education. Ultimately, this paper shows that probationary status during college is a channel of information to low ability students, who are becoming more informed, and at the end they are changing career paths.

5

Conclusions

This dissertation brings causal evidence on three topics in education and health.

In the first chapter, I study how a period of positive rainfall shocks, the 1982-1983 El Niño, affected the long-term education and health outcomes of individuals conceived and/or born around the time of the event. I employ site and timing variation in exposure to the event to compare cohorts of children exposed to the event with cohorts of children not exposed to the event. The results show that the 1982-1983 El Niño decreased the probability to have completed primary education of the exposed individuals at adulthood. I establish that the negative impacts of floods on education outcomes hold only for urban areas and in-utero exposure to the event. In contrast, I find an increase in total years of education for those individuals exposed to the floods in rural areas and a no significant effect for individuals exposed to the floods after birth. As a part of the analysis, I also compare two El Niño events one more predictable than the other, to investigate possible heterogeneous effects. The results show how important it is for individuals to cope with extreme weather conditions and that floods that were more unpredictable had detrimental effects on individuals' educational choices. Several robustness checks indicate that the results are unlikely to be driven by factors other than the excess rainfall shock due to the El Niño. Despite some data limitations, I explore possible mechanisms of prenatal exposure to floods on education outcomes. First, the finding that in-utero exposure to the event had significant effects on individuals' outcomes while post-birth exposure did not affect the same outcomes, may be an indicator of the nutrition channel in place. The floods brought destruction of roads and bridges reducing the intake of healthy food for pregnant women and leading to low weight at birth of newborns. It could also have increased maternal stress, which adversely affects the pregnancy outcome such as increased risk of morbidity for the child, and increase the risk for preterm birth.

This study builds on the literature on rainfall shocks and climate change by bringing new evidence using plausible exogenous variation in excess rainfall due to the event named El Niño in Peru. I use the abruptness of the climatology conditions (change in precipitation from the historical averages) to credible isolate the effect from other confounding behavioral responses.

Overall, the evidence I report is different from quasi-experimental studies from other countries where not only in-utero exposure to floods but also early in life exposure had either positive or negative effects on individuals' health and education outcomes.

This chapter also contributes to a body of research on the adaptation to climate change through the development of tools and technology to help individuals to cope with extreme weather conditions. It establishes that individuals' well-being also depends on prenatal conditions in developing countries, and the possibility to predict extreme climatology events could help individuals mitigate the negative impacts of climate change.

The second chapter brings causal evidence on how female role models affect individuals' career choices and perceptions. I study how a field experiment that randomly allocated students to female role models affected students' preferences for engineering programs and the underlying mechanisms in a context where predominant gender stereotypes exist. I find that female role models talks increased preferences for engineering majors of high math ability female senior high school students by 14 percentage points. I attribute this finding to the increased self-confidence in own aptitude and skills to perform well in engineering majors of high math ability girls exposed to the treatment. Given that the study demonstrates an increase in interest for engineering majors, in particular, the engineering majors of the role models, role models are a source of inspiration for girls. On the other hand, I also find a marginal and positive effect for low math ability boys exposed to the treatment of 6 percentage points. In the case of boys, the mechanism is less clear but seems to be related to the information provided in the talks, which stressed that skills other than math ability are also relevant in engineering majors. My results related to preferences and potential mechanisms are stronger among students that reside within the role models place of residence and university area. Thus, this study shows that the effects of role models are mostly local and that not everyone can be an effective role model in any type of context.

Previous research in developed countries suggests that the positive association between choices for STEM majors and exposure to female role models is explained by an increase in self-concept only. This study looks at alternative explanations, which include the content of the talks and the identity of the role models both of them reduce gender stereotypes in society and empower women and men to enroll in careers they may be good at based on their skills.

Finally, in the third chapter I study the effect of a misallocation of talent and education mismatches at college on students' outcomes using an exogenous variation introduced by academic probationary rules. A regression discontinuity design that uses a policy at university for academic probation as a deterministic function of GPA suggests that exposure to academic probation leads to higher attrition rates for men and women and negative effects on subsequent academic performance only for women choosing to stay in their programs. While the effects on attrition rates hold for both women and men, they are particularly strong for first year male students. To summarize, this chapter emphasizes: i) the importance of accounting for gender differences in responses to signals of ability when studying the consequences of academic probationary rules on education outcomes, ii) that in situations where there exist social pressure to pursue particular majors of study, university policies may be efficient to reduce educational mismatches and to increase aggregate productivity.

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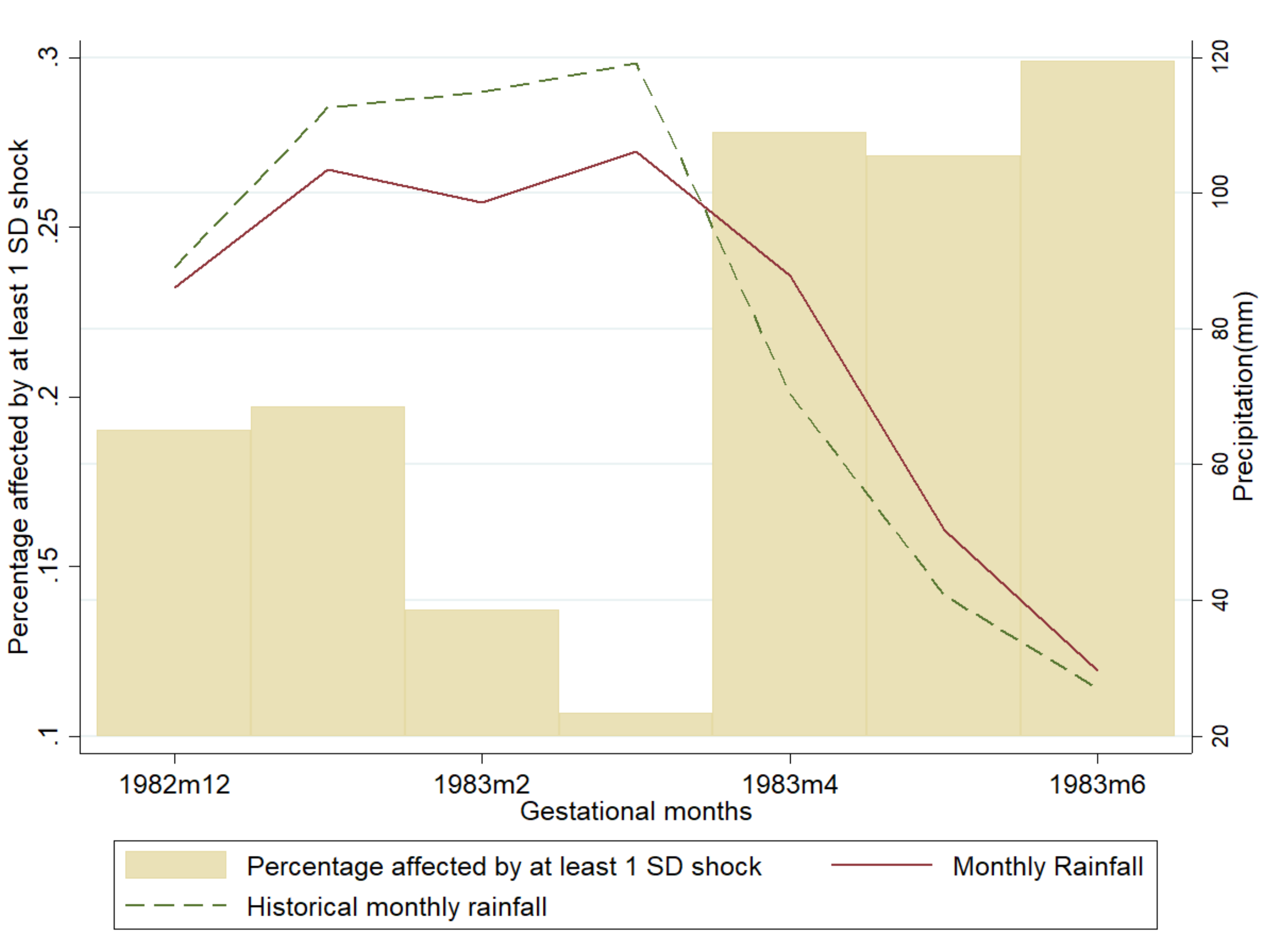
Appendices

Appendix A

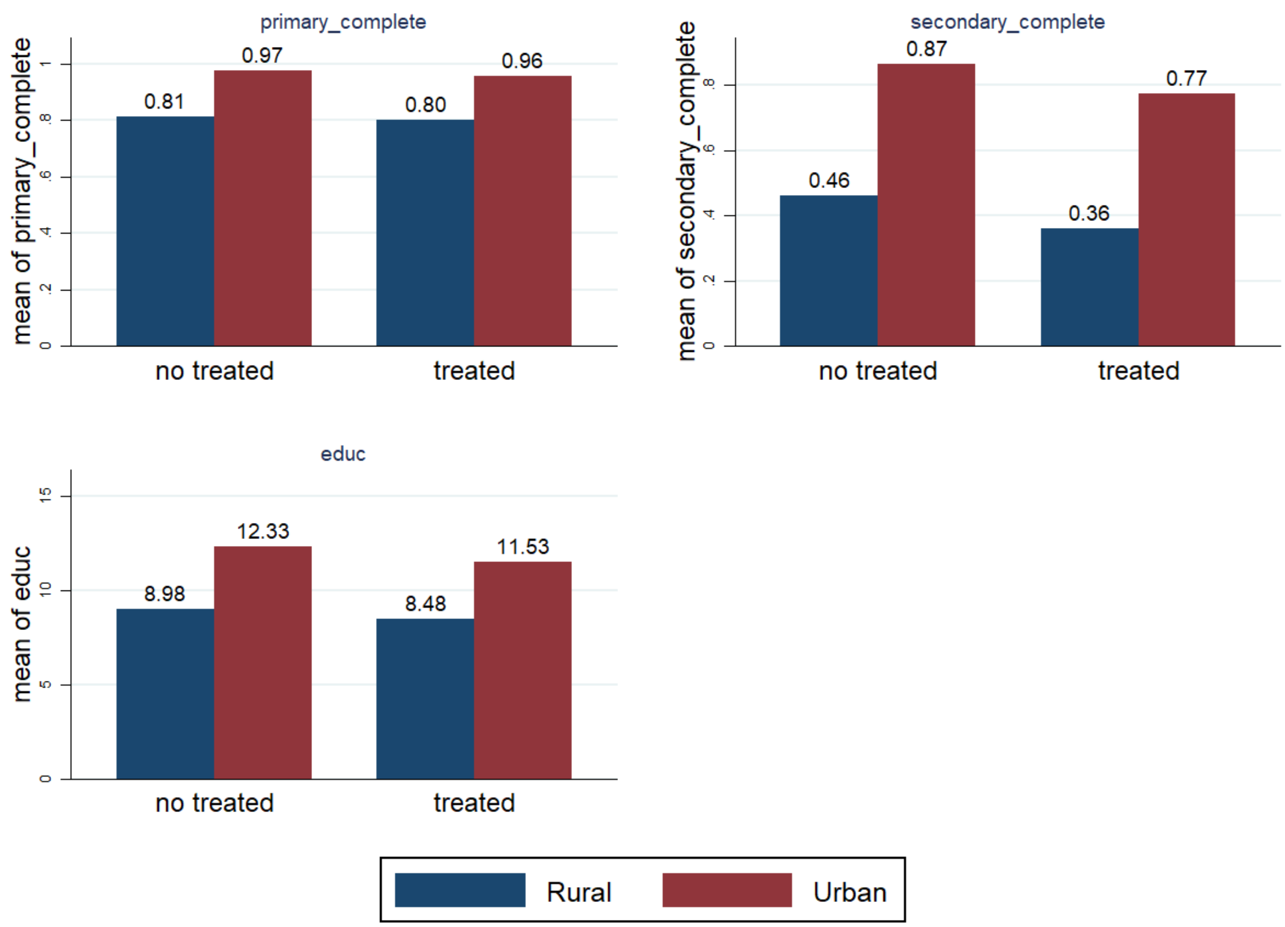
Figures and Tables

Figure A.1: Average monthly rainfall, historical mean and proportion of individuals hit by intense floods (positive rainfall shock) during the in-utero period and the 1982-1983 El Niño



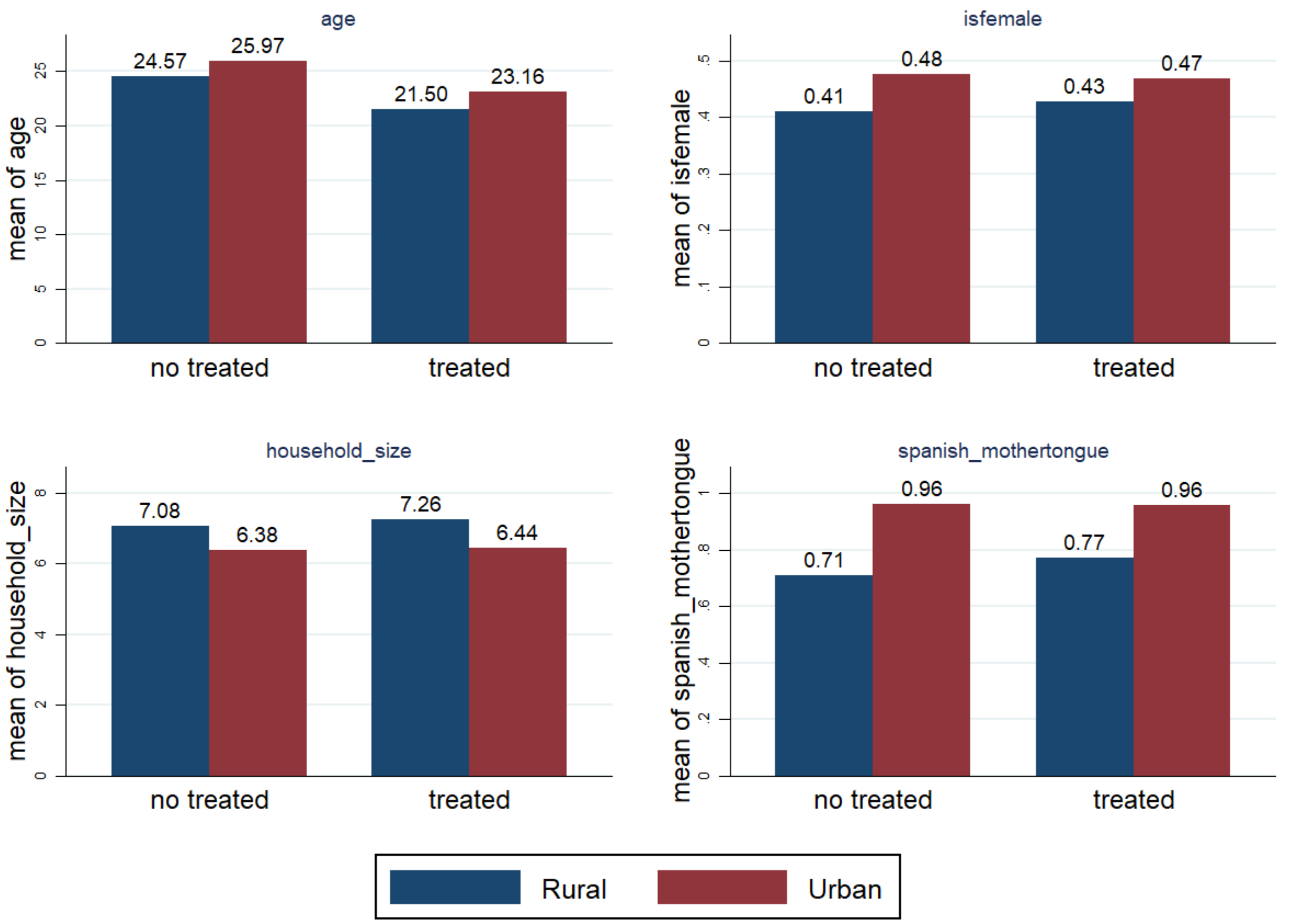
Notes: The monthly rainfall reported in the figure (solid line) is calculated averaging the monthly precipitation across the ENAHO districts for the period December 1982-June 1983. The historical monthly rainfall (dashed line) corresponds to the average monthly precipitation registered in each district (municipality) during the period 1970-2001. Rainfall is measured in millimetres and reported on the right y-axis. The bars represent the proportion of individuals exposed to intense floods (a positive rainfall shock of at least 1 SD) in each gestational month (left y-axis)

Figure A.2: Descriptive Statistics (1982-1983 El Niño): Dependent Variables



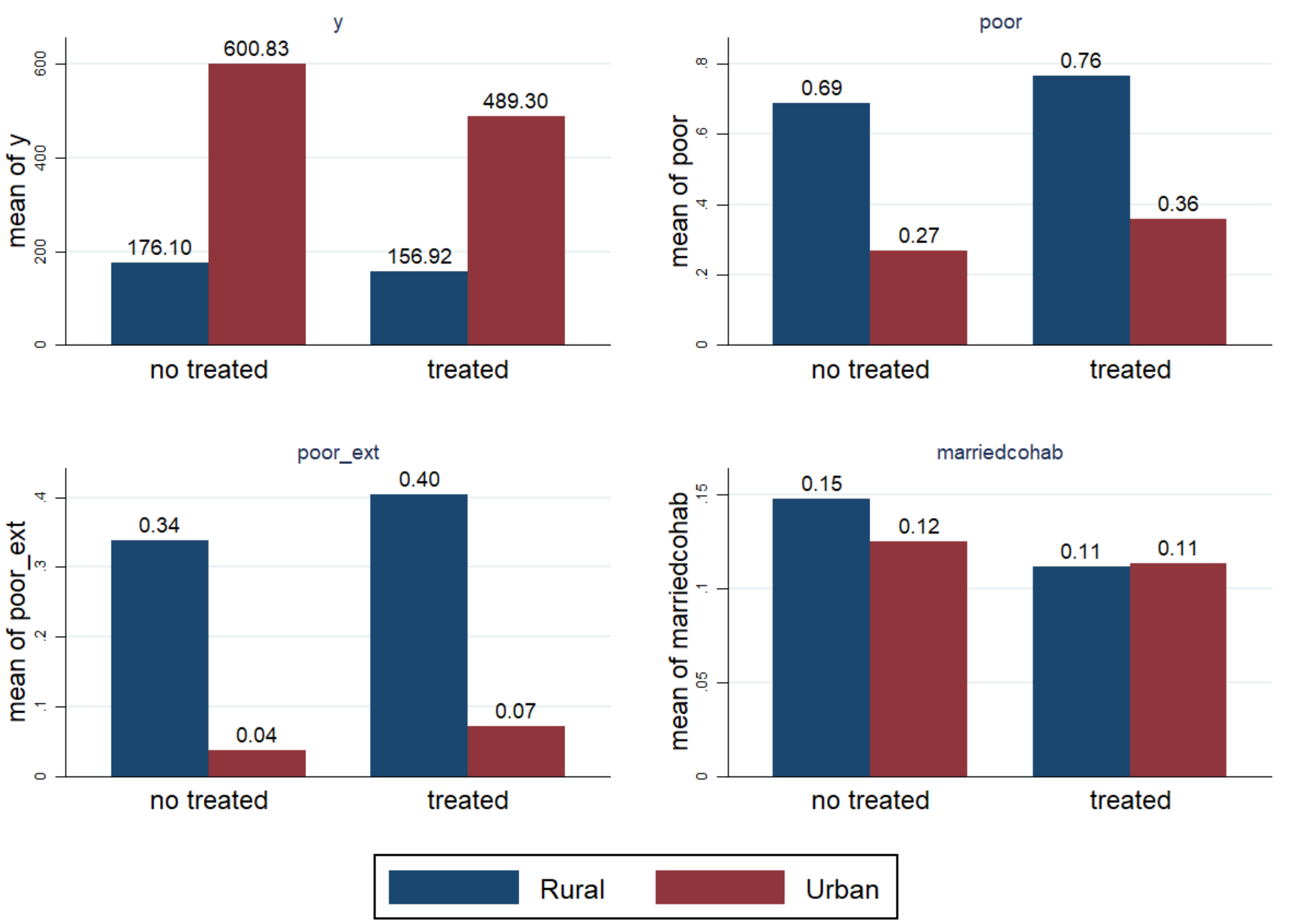
Notes: The figure shows summary statistics (average) of long-term educational outcomes by treatment status and zone of residence. "*primary_complete*" is a dummy variable that equals one if the individual reported to have completed primary education and zero otherwise. Similarly, "*secondary_complete*" is a dummy variable that equals one if the individual reported to have completed secondary education and zero otherwise. "*educ*" denotes total years of education completed by the individual.

Figure A.3: Descriptive Statistics (1982-1983 El Niño): Covariates



Notes: The figure shows summary statistics (average) of individual's demographic characteristics by treatment status and zone of residence.

Figure A.4: Descriptive Statistics (1982-1983 El Niño): Covariates (continued)

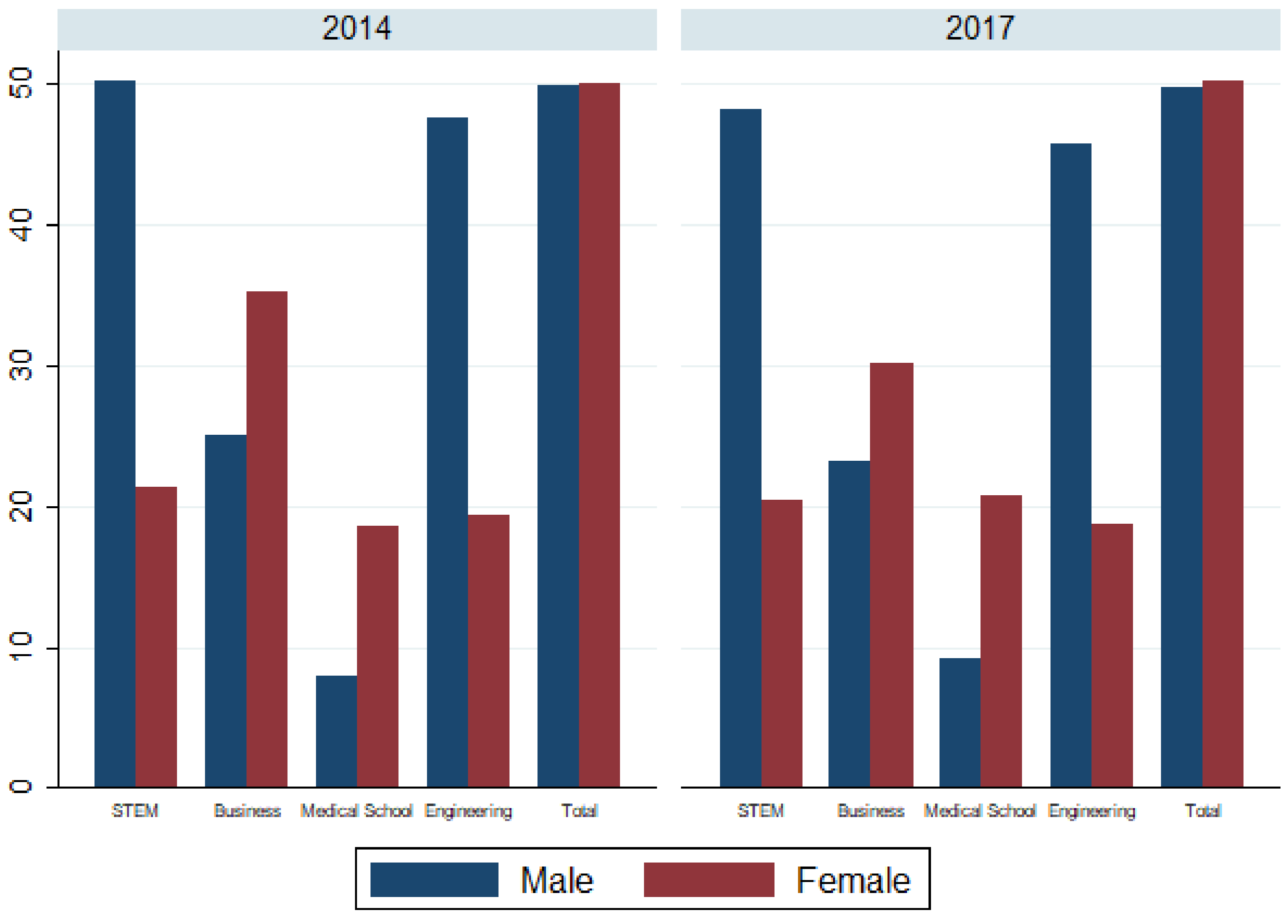


Notes: The figure shows summary statistics (average) of individuals and households' characteristics by treatment status and zone of residence."*y*" denotes net household monthly income per capita. "*poor*" and "*poor_ext*" are poor and extreme poor indicators for the household, respectively. "*marriedcohab*" is an indicator which equals one if the individual reported to be married or to reside with another as if married, and zero otherwise.

Figure A.5: Thumbnails of slides shown during school visits

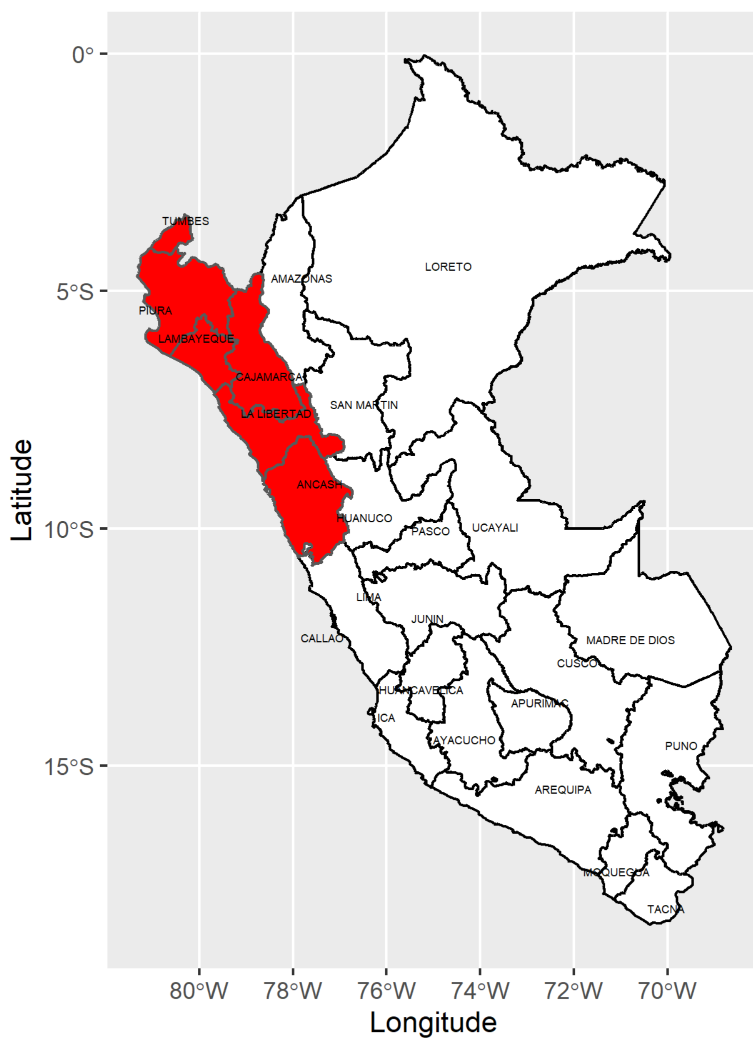
Figure A.6: Thumbnails of slides shown during school visits (continued)

Figure A.7: Share of male and female applicants to selective undergraduate academic programs for the whole population of applicants in 2014 and 2017, Peru



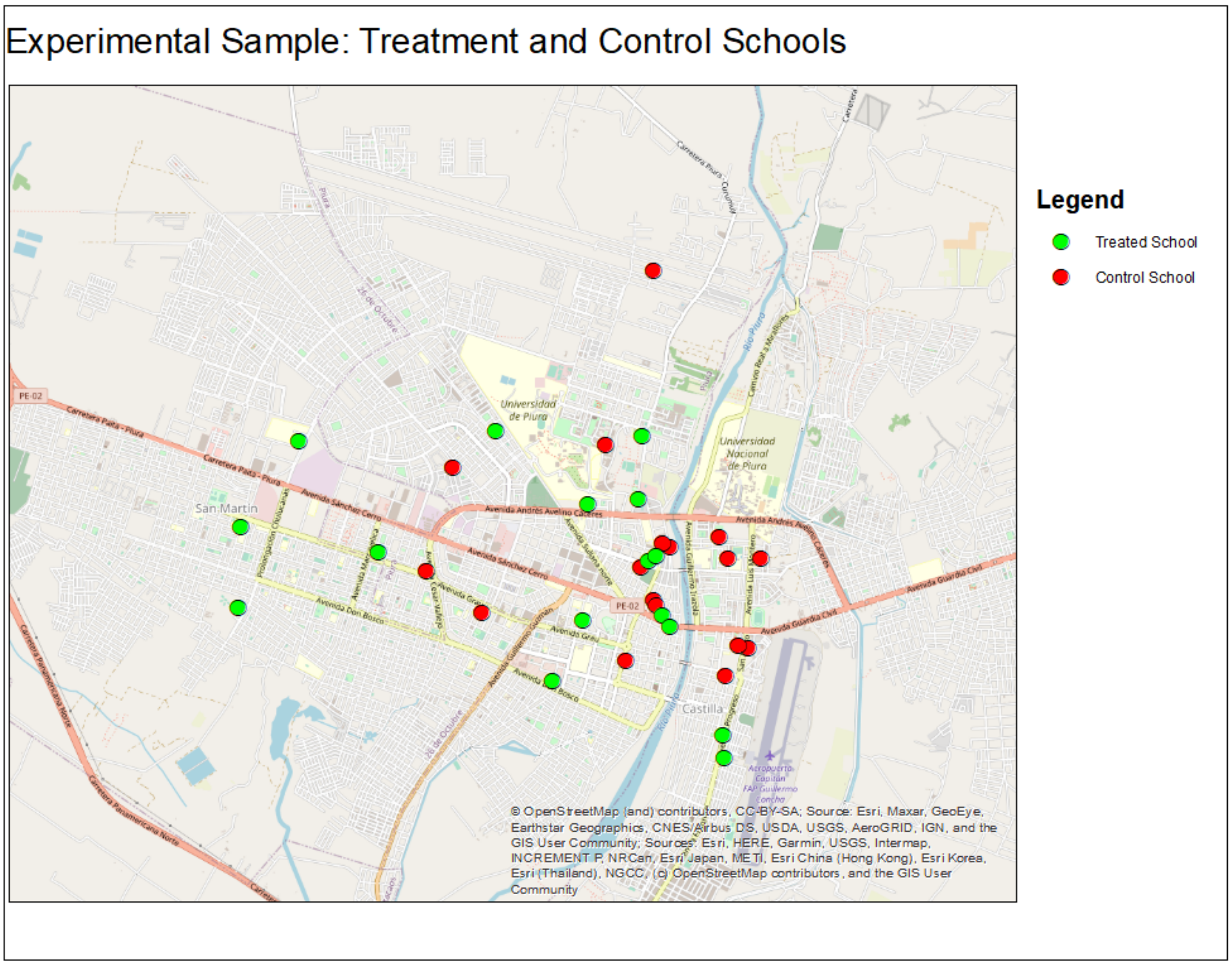
Notes: Data from public records of the Peruvian National Superintendence of Higher Education (SUNEDU): https://www.sunedu.gob.pe/sibe/.

Figure A.8: Experimental sample in Peru



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

Figure A.9: Experimental sample: Piura city



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

Figure A.10: Distribution of school ECE math scores

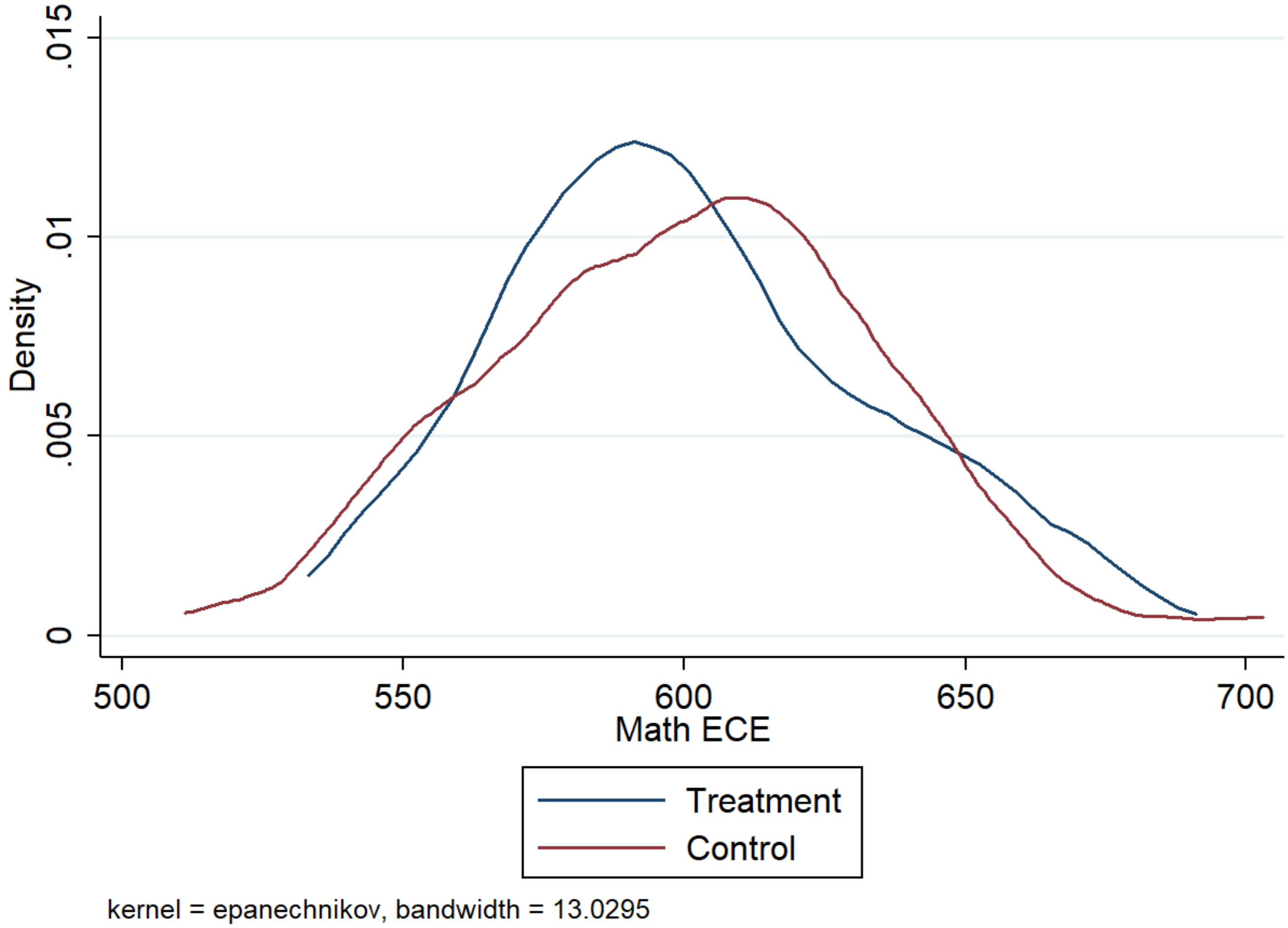
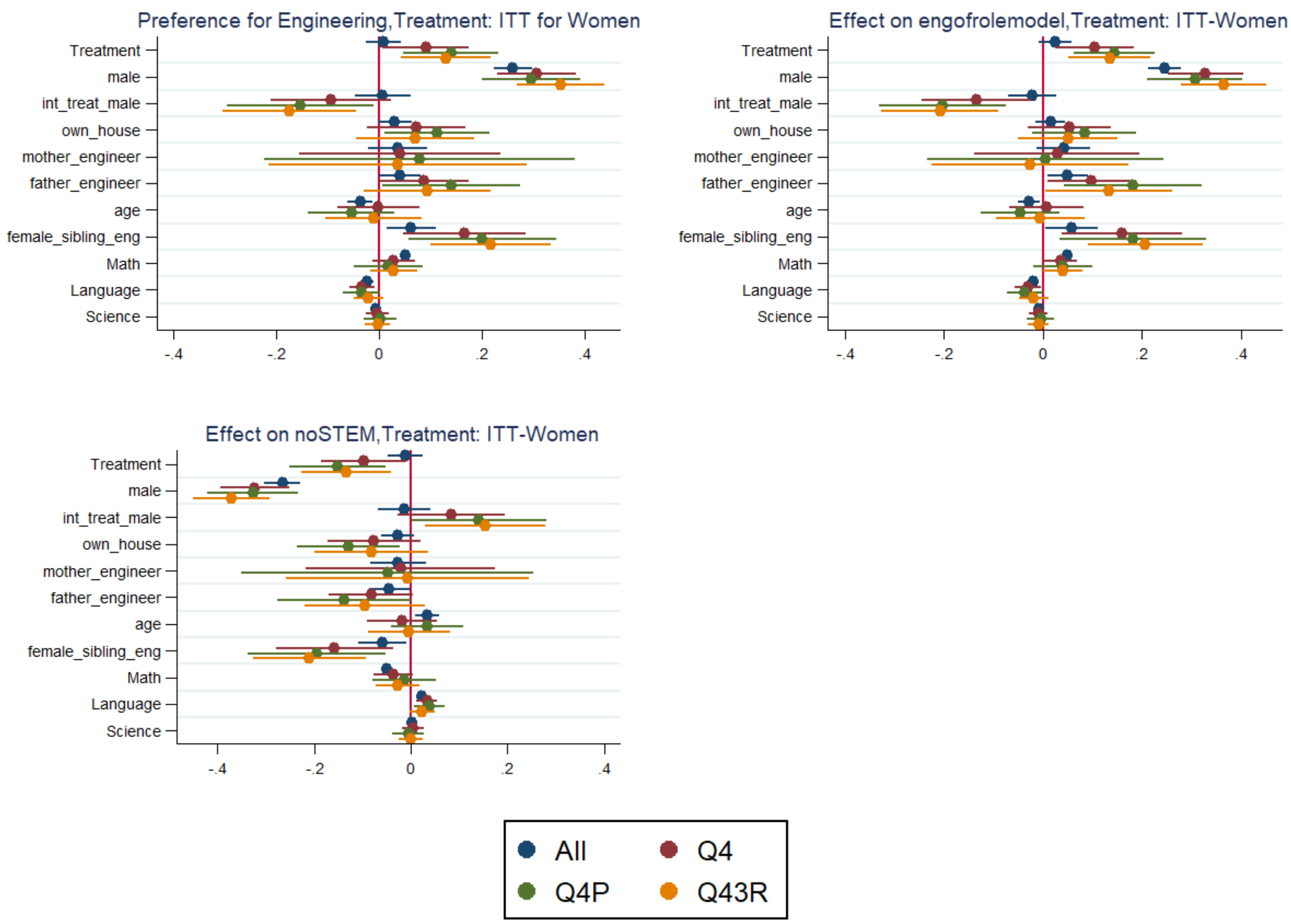
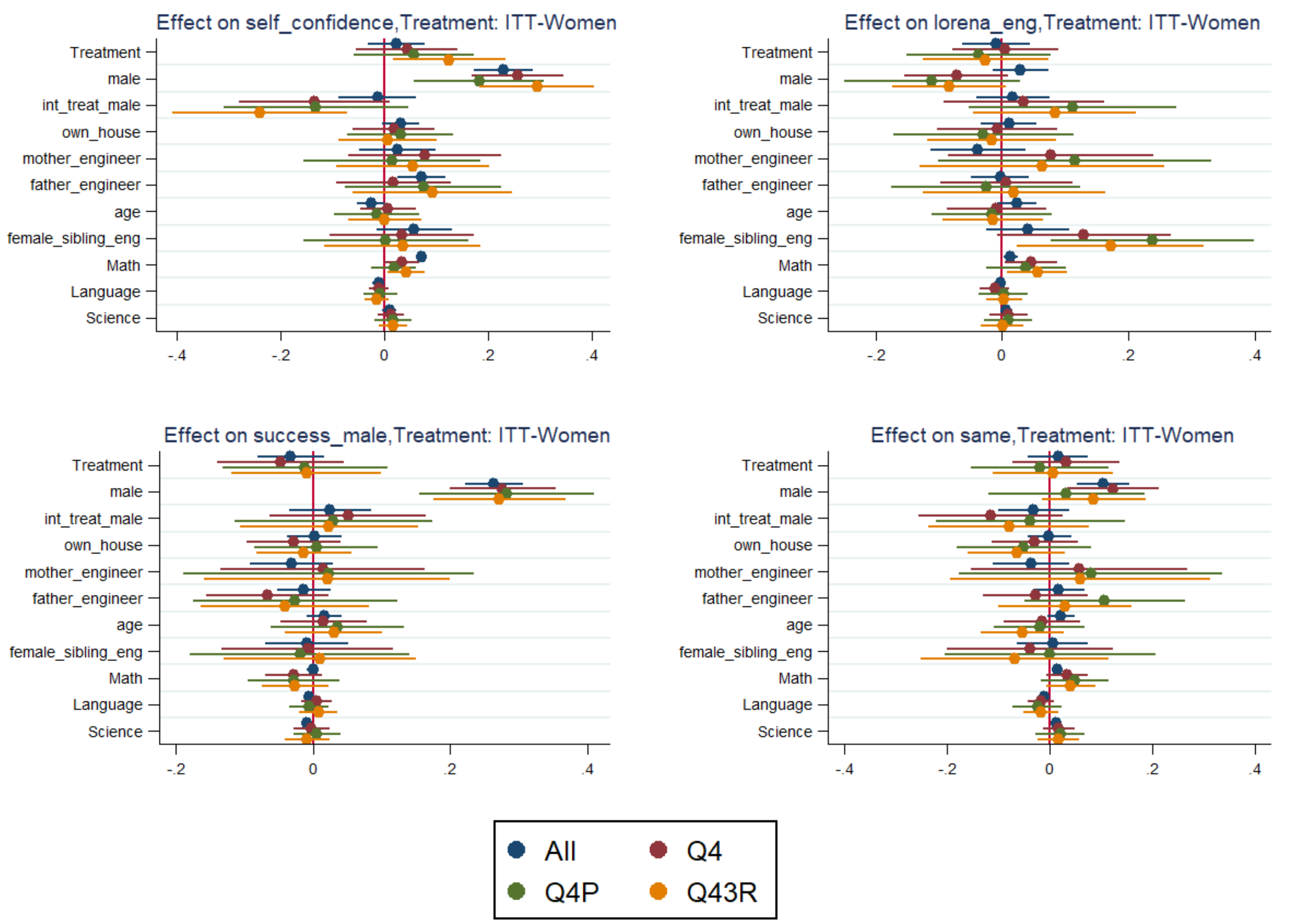


Figure A.11: Senior-year high school students- preference for fields of study



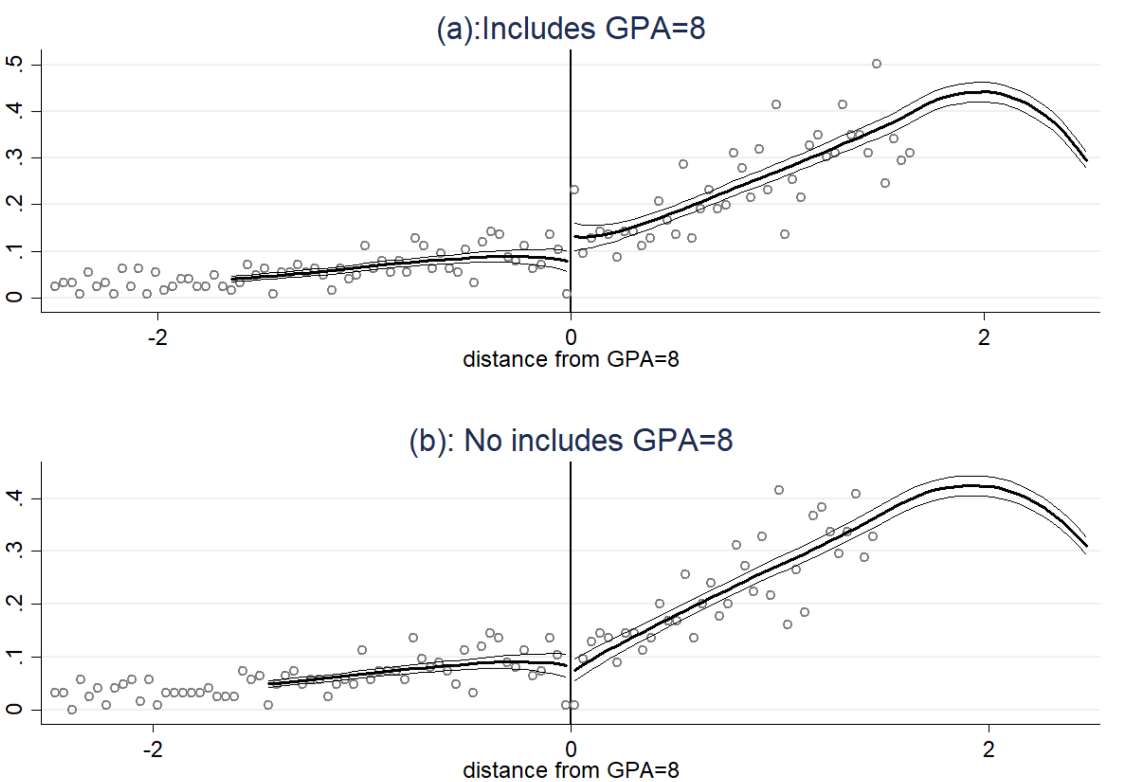
Notes: The figure shows the intent to treat (ITT) estimates for girls ("*Treatment*") and the effect of other covariates on senior-year students' preferences for fields of study: i) all types of Engineering, ii) the role models engineering majors (Industrial and Systems Engineering, Civil Engineering,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

Figure A.12: Senior-year high school students- perceptions



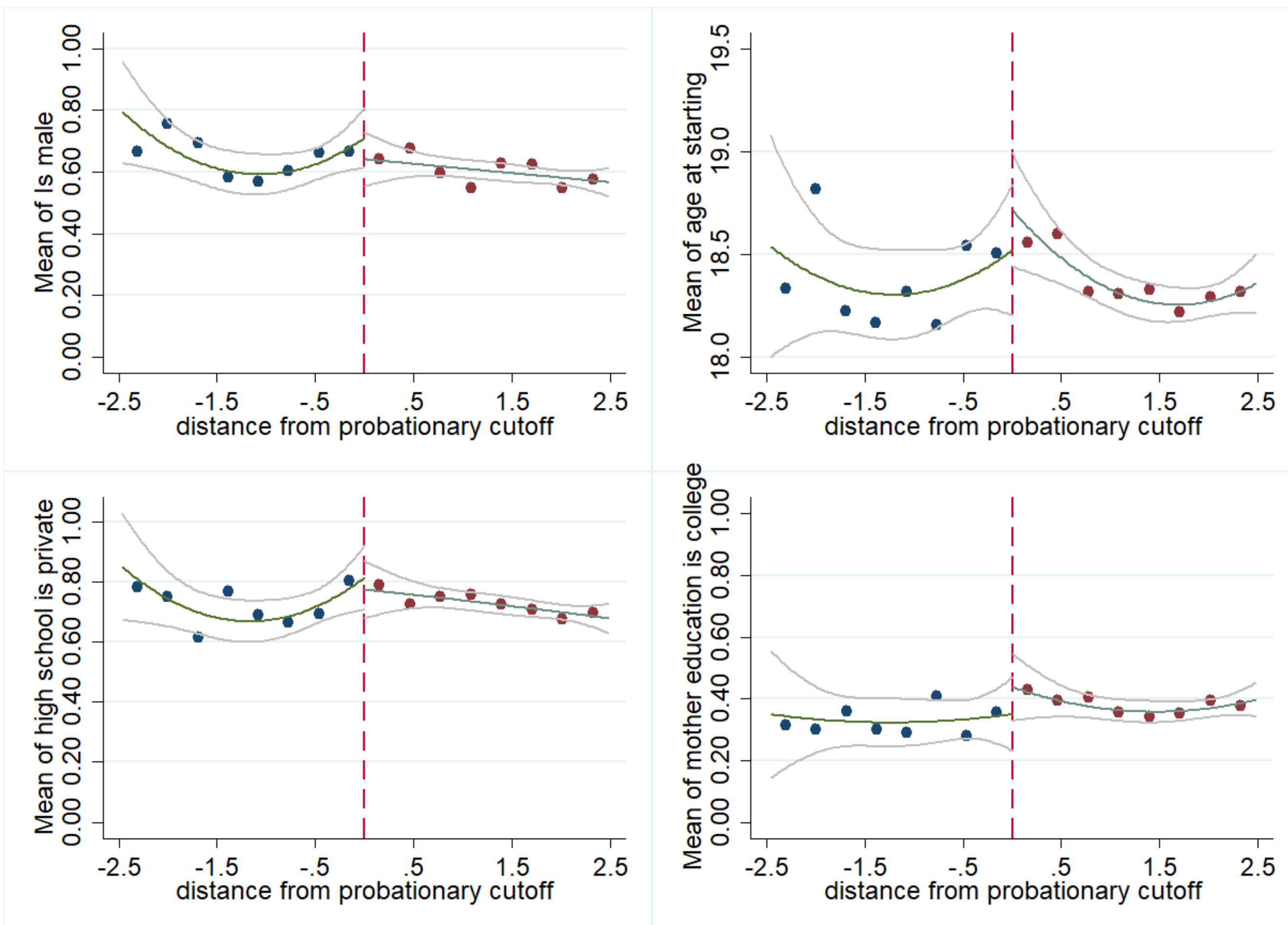
Notes: The figure shows the intent to treat (ITT) estimates for girls ("*Treatment*") and the effect of other covariates on senior-year students' perceptions: i) self-confidence in having aptitude and skills to pursue an engineering major, ii) recommending engineering to a hypothetical female friend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

Figure A.13: Manipulation test



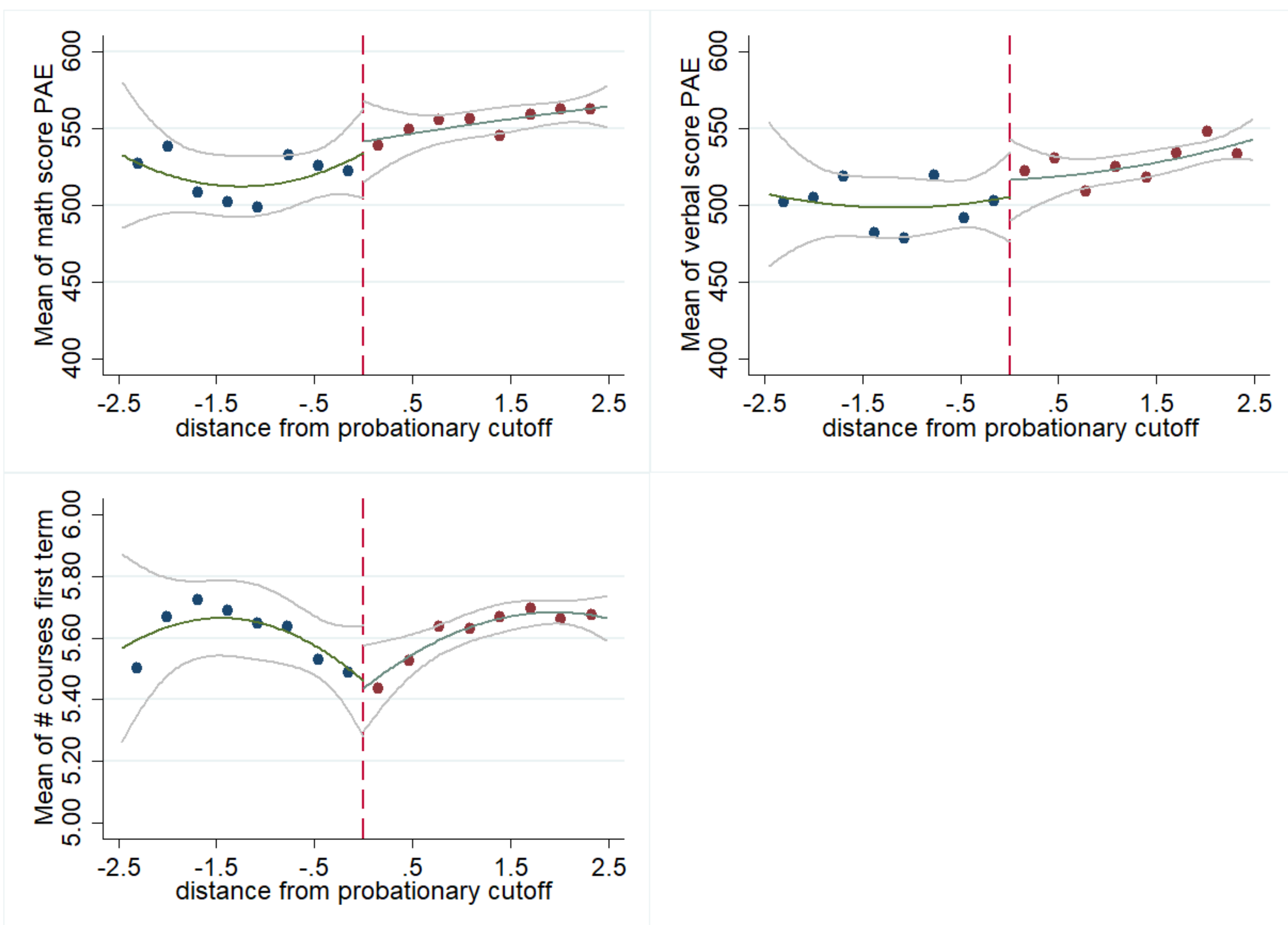
Notes: Each small hollow circle indicates the "density of probability." Intuitively, it shows the chance of obtaining values near corresponding points on the running_variable. The running_variable is the distance from the probationary cutoff of 8. The curve is predicted from local linear regressions with a recommended bandwidth of 0.82 in panel (a) and 0.99 in panel(b).The estimated discontinuity is 0.16 with a standard error of 0.20 using the sample that excludes observations with GPA of 8.

Figure A.14: Distribution of predetermined variables



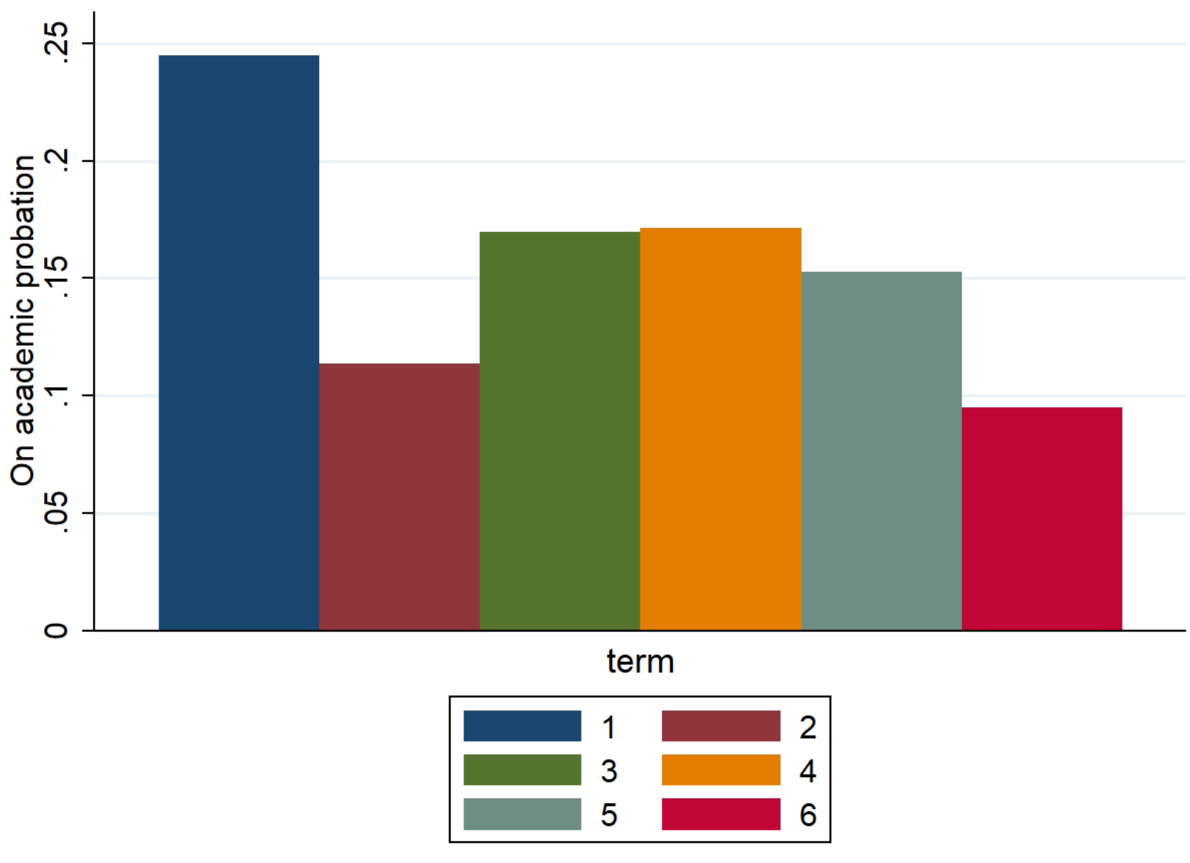
Notes: The red vertical line in each figure indicates the probationary cutoff, which is used as the university policy and normalized to 0. I use a 2.5 grade point distance GPA bandwidth on each side. The dots represent the means of predetermined variables for students in each term-year within 31.25% of a grade point in the restricted sample. The solid lines are fitted values using quadratic regressions. The gray colored lines are the 95 percent confidence intervals.

Figure A.15: Distribution of predetermined variables (continue)



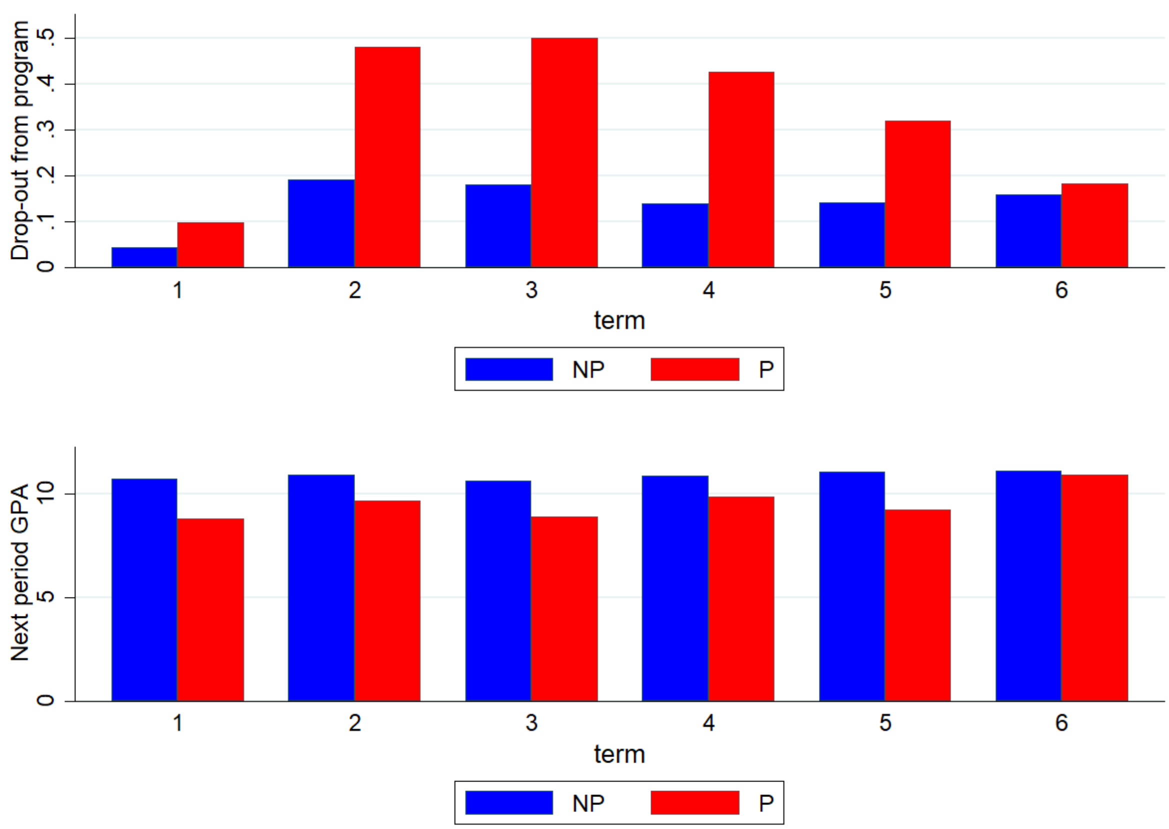
Notes: The red vertical line in each figure indicates the probationary cutoff, which is used as the university policy and normalized to 0. I use a 2.5 grade point distance GPA bandwidth on each side. The dots represent the means of predetermined variables for students in each term-year within 31.25% of a grade point in the restricted sample. The solid lines are fitted values using quadratic regressions. The gray colored lines are the 95 percent confidence intervals.

Figure A.16: Distribution of students on academic probation by term



Notes: The timing variable is "term" and it stands for each of the periods a student is observed in the restricted sample. The figure shows the proportion of students on academic probation by term.

Figure A.17: Distribution of outcome variables by term and academic probation status



Notes: The timing variable is "term" and it stands for each of the periods a student is observed in the restricted sample. "NP" and "P" denote no probation and probation status, respectively.

Table A.1: Intensity of El Niño (1997-1998): Other Outcomes

Dep. Variable:	Self-employment	Extreme Poor	Poor	Marital Status	Net HH Income pc	Chronic Disease
	(1)	(2)	(3)	(4)	(5)	(6)
Full Sample						
shock_inutero	0.0148	-0.00486*	-0.00233	0.0148	-8.584	0.0241**
	(0.0171)	(0.00280)	(0.00928)	(0.0214)	(11.66)	(0.0122)
Number of observations (N)	29,556	46,431	46,431	46,431	46,431	46,431
Adjusted R^2	0.039	0.189	0.239	0.059	0.255	0.057
Urban						
shock_inutero	0.0121	-0.00347	-0.00496	0.0170	-15.92	0.0297**
	(0.0227)	(0.00214)	(0.0103)	(0.0234)	(13.64)	(0.0145)
Number of observations (N)	18,395	31,994	31,994	31,994	31,994	31,994
Adjusted R^2	0.038	0.121	0.160	0.061	0.197	0.044
Rural						
shock_inutero	0.00909	-0.00840	0.0113	-0.00351	5.887	8.87e-05
	(0.0172)	(0.00983)	(0.0165)	(0.0727)	(15.13)	(0.0137)
Number of observations (N)	11,161	14,437	14,437	14,437	14,437	14,437
Adjusted R^2	0.044	0.190	0.285	0.057	0.225	0.055
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effect of intensity of exposure to the 1997-1998 El Niño on health and income variables for individuals born between 1990-1998 and who are older than 17 years old. The treatment variable is the number of months of exposure to intense floods. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A.2: Intensity of El Niño (1982-1983): Other Outcomes

Dep. Variable:	Self-employment	Extreme Poor	Poor	Marital Status	Net HH Income pc	Chronic Disease
	(1)	(2)	(3)	(4)	(5)	(6)
Full Sample						
shock_inutero	-0.00976*	-0.00182	-0.00413	0.00774	1.873	-0.00443
	(0.00553)	(0.00231)	(0.00611)	(0.0186)	(8.126)	(0.00466)
Number of observations (N)	26,261	35,981	35,981	35,971	35,981	35,981
Adjusted R^2	0.043	0.351	0.298	0.091	0.289	0.127
Urban						
shock_inutero	-0.0126*	-0.00335	-0.00506	0.00861	1.889	-0.00455
	(0.00656)	(0.00217)	(0.00704)	(0.00656)	(9.460)	(0.00539)
Number of observations (N)	19,320	27,546	27,546	27,539	27,546	27,546
Adjusted R^2	0.041	0.248	0.220	0.097	0.244	0.124
Rural						
shock_inutero	0.000648	-0.00167	0.000202	0.0213	5.999*	-0.00272
	(0.00884)	(0.0105)	(0.0110)	(0.0384)	(3.481)	(0.0104)
Number of observations (N)	6,941	8,435	8,435	8,432	8,435	8,435
Adjusted R^2	0.100	0.298	0.331	0.110	0.276	0.169
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports the effect of intensity of exposure to the 1982-1983 El Niño on health and income variables for individuals born between 1975-1983 and who are older than 17 years old. The treatment variable is the number of months of exposure to intense floods. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A.3: The effect of both In-Utero and Early in Life Exposure to El Niño on Secondary Education Completion

Dep. Variable:	**Secondary Education Completion**					
	Full	Full	Urban	Urban	Rural	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sample: Born between 1975-1983						
treatment_inutero	0.000885	0.000993	-0.0136	-0.0146	0.0931**	0.0962***
	(0.0128)	(0.0125)	(0.0142)	(0.0142)	(0.0371)	(0.0370)
treatment_2y	0.0123	0.0137	0.0123	0.0127	0.00428	0.00423
	(0.0109)	(0.0111)	(0.0117)	(0.0118)	(0.0281)	(0.0285)
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Number of observations (N)	35,977	35,977	27,543	27,543	8,434	8,434
Adjusted R^2	0.238	0.266	0.149	0.151	0.234	0.237

Notes: This table reports the effect of in-utero exposure and early in life exposure to the 1982-1983 El Niño on secondary education completion for individuals born between 1975-1983 and who are older than 17 years old. The variable treatment_inutero equals one if the individual was exposed to the 1982-1983 El Niño while in-utero, and zero otherwise. The variable treatment_2y equals one if the individual was exposed to the 1982-1983 El Niño after birth up to two years old, and zero otherwise. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.4: The effect of both In-Utero and Early in Life Exposure to El Niño on Primary Education Completion

Dep. Variable:	**Primary Education Completion**					
	Full	Full	Urban	Urban	Rural	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sample: Born between 1975-1983						
treatment_inutero	-0.00197	-0.00141	-0.0144**	-0.0144**	0.0305	0.0358
	(0.00813)	(0.00807)	(0.00690)	(0.00689)	(0.0311)	(0.0310)
treatment_2y	0.00664	0.00679	0.00106	0.00103	0.0234	0.0237
	(0.00647)	(0.00639)	(0.00535)	(0.00538)	(0.0225)	(0.0225)
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Number of observations (N)	36,053	36,053	27,593	27,593	8,460	8,460
Adjusted R^2	0.173	0.186	0.094	0.094	0.181	0.197

Notes: This table reports the effect of in-utero exposure and early in life exposure to the 1982-1983 El Niño on primary education completion for individuals born between 1975-1983. The variable treatment_inutero equals one if the individual was exposed to the 1982-1983 El Niño while in-utero, and zero otherwise. The variable treatment_2y equals one if the individual was exposed to the 1982-1983 El Niño after birth up to two years old, and zero otherwise. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.5: Balance in covariates: 1982-1983 El Niño

	Control Group	Treatment Group	Dif T-C	Dif T-C	Dif T-C	Dif T-C	Dif T-C
Sample:	Full	Full	Full	Urban	Rural	Female	Male
Dep Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
sewage	0.799	0.680	-0.0114	-0.00545	-0.0346	-0.0192	-0.00487
			(0.00939)	(0.0105)	(0.0274)	(0.0172)	(0.0145)
water	0.815	0.703	-0.00568	-0.0160	0.0133	-0.0157	0.00400
			(0.0110)	(0.0116)	(0.0221)	(0.0167)	(0.0155)
electricity	0.888	0.781	-0.000857	-0.00614	0.0174	-0.00946	0.00559
			(0.00826)	(0.00698)	(0.0230)	(0.0106)	(0.0127)
household_size	6.487	6.646	-0.0138	-0.0380	0.0841	-0.133	0.0839
			(0.0739)	(0.0884)	(0.160)	(0.110)	(0.0951)
poor_extreme	0.083	0.156	0.00820	0.00419	-0.00975	0.0131	0.00256
			(0.00731)	(0.00690)	(0.0268)	(0.0127)	(0.0106)
poor	0.334	0.461	0.00679	0.00435	0.0236	0.00276	0.0163
			(0.0154)	(0.0179)	(0.0271)	(0.0208)	(0.0210)
urban	0.846	0.746	-0.000351			-0.00831	0.00754
			(0.00918)			(0.0139)	(0.0138)
age in years	25.75	22.74	-0.0163	-0.0239	0.0277	-0.0135	-0.0214
			(0.0177)	(0.0204)	(0.0250)	(0.0245)	(0.0261)
isfemale	0.467	0.458	0.0307*	0.0303	0.0465		
			(0.0169)	(0.0197)	(0.0367)		
spanish	0.928	0.919	0.00643	0.00426	-0.0123	0.0256	-0.0142
			(0.00979)	(0.0108)	(0.0261)	(0.0156)	(0.0121)
mother_moreprimary	0.333	0.239	-0.0242*	-0.0280*	-0.00301	-0.0727***	0.0188
			(0.0136)	(0.0162)	(0.0111)	(0.0247)	(0.0243)
father_moreprimary	0.466	0.350	-0.0329**	-0.0290*	-0.0194	-0.0234	-0.0453**
			(0.0149)	(0.0170)	(0.0211)	(0.0234)	(0.0201)
Test of joint significance		F-stat: 1.11 (p-value: 0.348)					

Notes: Column 1 and column 2 report the sample mean for individuals in the control and in the treatment group, respectively. The sample is restricted to individuals born between 1975-1983. Columns 3-7 display the estimate on the treatment dummy in a regression of each variable on treatment. The regression controls for cohort of birth fixed effects, province of residence fixed effects, district of birth fixed effects, and survey year fixed effects. Standard errors clustered at the district of birth are shown in parentheses. A test for the joint significance of the coefficients is performed after running a regression of the treatment dummy on the baseline covariates. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A.6: Balance in covariates: 1997-1998 El Niño

	Control Group	Treatment Group	Dif T-C	Dif T-C	Dif T-C	Dif T-C	Dif T-C
Sample:	Full	Full	Full	Urban	Rural	Female	Male
Dep Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
sewage	0.754	0.735	0.0127	-0.0216	0.0611*	-0.0136	0.0373
			(0.0168)	(0.0167)	(0.0337)	(0.0246)	(0.0234)
water	0.811	0.865	-0.00708	-0.0114	-0.00200	-0.0223	0.0128
			(0.0174)	(0.0170)	(0.0327)	(0.0269)	(0.0231)
electricity	0.928	0.951	-0.000184	-0.00308	0.00188	-0.0114	0.0109
			(0.00844)	(0.00515)	(0.0279)	(0.0112)	(0.0117)
household_size	5.697	5.363	-0.112	-0.121	0.125	-0.191	-0.0286
			(0.0816)	(0.0959)	(0.156)	(0.137)	(0.111)
poor_extreme	0.040	0.024	-0.00645	-0.00391	-0.0155	-0.00426	-0.00608
			(0.00684)	(0.00471)	(0.0208)	(0.00858)	(0.0106)
poor	0.202	0.140	-0.0167	-0.0199	-0.00905	0.0111	-0.0315
			(0.0151)	(0.0156)	(0.0312)	(0.0207)	(0.0211)
urban	0.782	0.779	-0.00169			-0.0128	0.0105
			(0.0142)			(0.0198)	(0.0189)
age in years	19.69	17.78	-0.0223	0.000692	-0.0730**	-0.0216	-0.00936
			(0.0219)	(0.0283)	(0.0296)	(0.0300)	(0.0313)
isfemale	0.463	0.460	-0.0586**	-0.0488	-0.0586		
			(0.0271)	(0.0338)	(0.0372)		
spanish	0.885	0.884	-0.00468	0.00511	-0.0340	-0.0190	0.00786
			(0.0140)	(0.0152)	(0.0277)	(0.0248)	(0.0153)
mother_moreprimary	0.397	0.433	0.0164	0.0208	0.00840	-0.0146	0.0435
			(0.0260)	(0.0330)	(0.0223)	(0.0384)	(0.0320)
father_moreprimary	0.529	0.558	0.0246	0.0244	0.0470	0.00968	0.0407
			(0.0220)	(0.0273)	(0.0300)	(0.0346)	(0.0280)
Test of joint significance		F-stat: 0.93 (p-value: 0.520)					

Notes: Column 1 and column 2 report the sample mean for individuals in the control and in the treatment group, respectively. The sample is restricted to individuals born between 1990-1998 and who are older than 16 years old. Columns 3-7 display the estimate on the treatment dummy in a regression of each variable on treatment. The regression controls for cohort of birth fixed effects, province of residence fixed effects, district of birth fixed effects, and survey year fixed effects. Standard errors clustered at the district of birth are shown in parentheses. A test for the joint significance of the coefficients is performed after running a regression of the treatment dummy on the baseline covariates. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.7: Falsification Test: El Niño 1985-1986

	Full	Full	Urban	Urban	Rural	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
Sample: Born between 1985-1988						
Panel A: Primary Education Completion						
treatment_inutero	0.00746	0.00703	0.00366	0.00371	0.0321	0.0286
	(0.00608)	(0.00605)	(0.00561)	(0.00563)	(0.0207)	(0.0203)
Number of observations (N)	33,664	33,664	23,454	23,454	10,210	10,210
Adjusted R^2	0.143	0.148	0.124	0.124	0.144	0.155
Panel B: Secondary Education Completion						
treatment_inutero	0.00416	0.00424	0.00134	0.00188	0.0230	0.0198
	(0.0128)	(0.0126)	(0.0147)	(0.0147)	(0.0308)	(0.0309)
Number of observations (N)	29,178	29,178	20,705	20,705	8,473	8,473
Adjusted R^2	0.240	0.267	0.137	0.141	0.246	0.249
Panel C: Years of Education						
treatment_inutero	0.0149	0.0116	0.0152	0.0217	0.126	0.119
	(0.0624)	(0.0623)	(0.0741)	(0.0751)	(0.127)	(0.127)
Number of observations (N)	46,374	46,374	31,233	31,233	15,141	15,141
Adjusted R^2	0.524	0.541	0.513	0.517	0.398	0.401
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: This table reports the effect of in-utero exposure to a placebo 1985-1986 El Niño on primary education completion (Panel A), on secondary education completion (Panel B), and on total years of education (Panel C) for individuals born between 1985-1988. The variable treatment_inutero equals one if the individual was exposed to a false El Niño of 1985-1986 while in-utero, and zero otherwise. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A.8: Falsification Test: El Niño 2000-2001

Dep. Variable:	educ	educ	educ	educ	educ	educ	primary	primary
Sample	Full	Full	Urban	Urban	Rural	Rural	Full	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Sample: Born between 2000-2003								
treatment_inutero	0.00218	0.000365	-0.00507	-0.00679	0.0180	0.0171	0.00162	-0.00164
	(0.0259)	(0.0254)	(0.0332)	(0.0331)	(0.0377)	(0.0377)	(0.00570)	(0.0168)
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations (N)	51,149	51,149	28,376	28,376	22,773	22,773	723	723
Adjusted R^2	0.901	0.903	0.922	0.922	0.862	0.862	0.609	0.609

Notes: This table reports the effect of in-utero exposure to a placebo 2000-2001 El Niño on education outcomes for individuals born between 2000-2003. The variable treatment_inutero equals one if the individual was exposed to the 2000-2001 El Niño while in-utero, and zero otherwise. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table A.9: The effect of the 1982-1983 El Niño on Primary Education Completion: Heterogeneous Effects (by gender)

Sample: Born between 1975-1983						
Dep. Variable:	**Primary Education Completion**					
	Men	Men	Men Urban	Men Urban	Men Rural	Men Rural
	(1)	(2)	(3)	(4)	(5)	(6)
shock_inutero	-0.00191	-0.00247	-0.0105***	-0.0105***	0.0387***	0.0387***
	(0.00413)	(0.00402)	(0.00382)	(0.00382)	(0.0137)	(0.0138)
Number of observations (N)	19,702	19,702	14,622	14,622	5,080	5,080
Adjusted R^2	0.154	0.162	0.093	0.092	0.162	0.161
	Women	Women	Women Urban	Women Urban	Women Rural	Women Rural
	(1)	(2)	(3)	(4)	(5)	(6)
shock_inutero	-0.000113	-0.000101	-0.00130	-0.00131	0.0165	0.0166
	(0.00481)	(0.00475)	(0.00379)	(0.00378)	(0.0247)	(0.0246)
Number of observations (N)	16,351	16,351	12,971	12,971	3,380	3,380
Adjusted R^2	0.277	0.291	0.176	0.176	0.275	0.276
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: This table reports the effect of intensity of exposure to the 1982-1983 El Niño on primary education completion for individuals born between 1975-1983. The treatment variable is the number of months of exposure to intense floods. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table A.10: The effect of the 1982-1983 El Niño on Secondary Education Completion: Heterogeneous Effects (by gender)

Sample: Born between 1975-1983						
Dep. Variable:	**Secondary Education Completion**					
	Men	Men	Men Urban	Men Urban	Men Rural	Men Rural
	(1)	(2)	(3)	(4)	(5)	(6)
treatment_inutero	0.0108	0.00921	-0.00946	-0.00920	0.0932**	0.0932**
	(0.0196)	(0.0194)	(0.0232)	(0.0232)	(0.0434)	(0.0433)
Number of observations (N)	19,667	19,667	14,600	14,600	5,067	5,067
Adjusted R^2	0.218	0.244	0.143	0.143	0.244	0.244
Mean Dv (Treatment==0)	0.78	0.78	0.84	0.84	0.48	0.48
	Women	Women	Women Urban	Women Urban	Women Rural	Women Rural
	(1)	(2)	(3)	(4)	(5)	(6)
treatment_inutero	-0.0189	-0.0164	-0.0271	-0.0275	0.0629	0.0633
	(0.0201)	(0.0202)	(0.0209)	(0.0209)	(0.0695)	(0.0695)
Number of observations (N)	16,310	16,310	12,943	12,943	3,367	3,367
Adjusted R^2	0.305	0.333	0.203	0.203	0.303	0.302
Mean Dv (Treatment==0)	0.83	0.83	0.89	0.89	0.43	0.43
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: This table reports the treatment effects estimates on secondary education completion for individuals born between 1975-1983 and who are older than 17 years old. Column 1, column 3, and column 5 show the estimates without control variables while control variables are added in Column 2, column 4, and column 6. Each regression includes survey-year fixed effect, district of birth fixed effect, cohort of birth fixed effects, and province of residence fixed effect. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.11: The effect of the 1997-1998 El Niño on Primary Education Completion: Heterogeneous Effects (by gender)

Sample: Born between 1990-1998						
Dep. Variable:	**Primary Education Completion**					
	Men	Men	Men Urban	Men Urban	Men Rural	Men Rural
	(1)	(2)	(3)	(4)	(5)	(6)
treatment_inutero	0.00879	0.00848	0.0191***	0.0192***	-0.0232	-0.0237
	(0.00647)	(0.00648)	(0.00661)	(0.00663)	(0.0166)	(0.0167)
Number of observations (N)	31,755	31,755	20,658	20,658	11,097	11,097
Adjusted R^2	0.081	0.083	0.094	0.095	0.070	0.070
Mean Dv (Treatment==0)	0.97	0.97	0.98	0.98	0.94	0.94
	Women	Women	Women Urban	Women Urban	Women Rural	Women Rural
	(1)	(2)	(3)	(4)	(5)	(6)
treatment_inutero	0.00892	0.00949	0.0103	0.0102	0.0148	0.0147
	(0.0103)	(0.0104)	(0.0125)	(0.0125)	(0.0244)	(0.0244)
Number of observations (N)	26,612	26,612	18,478	18,478	8,134	8,134
Adjusted R^2	0.107	0.114	0.080	0.080	0.127	0.127
Mean Dv (Treatment==0)	0.97	0.97	0.99	0.99	0.92	0.92
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: This table reports the treatment effects estimates on primary education completion for individuals born between 1990-1998 and who are older than 16 years old. Column 1, column 3, and column 5 show the estimates without control variables while control variables are added in Column 2, column 4, and column 6. Each regression includes survey-year fixed effect, district of birth fixed effect, cohort of birth fixed effects, and province of residence fixed effect. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.12: The effect of the 1982-1983 El Niño on Primary Education Completion: Heterogeneous Effects (by parental education)

Dep. Variable:	Primary Education Completion					
	Mother no primary educ	Mother no primary educ	Mother no primary educ Urban	Mother no primary educ Urban	Mother no primary educ Rural	Mother no primary educ Rural
	(1)	(2)	(3)	(4)	(5)	(6)
treatment_inutero	-0.000483	-0.00101	-0.0188*	-0.0188*	0.0238	0.0241
	(0.0106)	(0.0106)	(0.00959)	(0.00960)	(0.0304)	(0.0304)
Number of observations (N)	26,151	26,151	17,987	17,987	8,164	8,164
Adjusted R^2	0.169	0.179	0.098	0.098	0.176	0.176
	Father no primary educ	Father no primary educ	Father no primary educ Urban	Father no primary educ Urban	Father no primary educ Rural	Father no primary educ Rural
	(1)	(2)	(3)	(4)	(5)	(6)
treatment_inutero	-0.00311	-0.00340	-0.0257**	-0.0257**	0.0242	0.0243
	(0.0124)	(0.0125)	(0.0117)	(0.0117)	(0.0323)	(0.0322)
Number of observations (N)	21,379	21,379	13,716	13,716	7,663	7,663
Adjusted R^2	0.177	0.185	0.126	0.126	0.174	0.174
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: This table reports the treatment effects estimates on primary education completion for individuals born between 1975-1983 and who are older than 16 years old. Column 1, column 3, and column 5 show the estimates without control variables while control variables are added in Column 2, column 4, and column 6. Each regression includes survey-year fixed effect, district of birth fixed effect, cohort of birth fixed effects, and province of residence fixed effect. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.13: The effect of the 1982-1983 El Niño on Primary Education Completion (continued): Heterogeneous Effects (by parental education)

Dep. Variable:	Primary Education Completion					
	Father primary educ	Father primary educ	Father primary educ Urban	Father primary educ Urban	Father primary educ Rural	Father primary educ Rural
	(1)	(2)	(3)	(4)	(5)	(6)
treatment_inutero	-0.00287	-0.00297	-0.00383	-0.00385	-0.00738	-0.00831
	(0.00504)	(0.00501)	(0.00485)	(0.00485)	(0.0911)	(0.0901)
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Number of observations (N)	14,674	14,674	13,877	13,877	797	797
Adjusted R^2	0.032	0.032	0.008	0.008	0.128	0.135

Notes: This table reports the treatment effects estimates on primary education completion for individuals born between 1975-1983 and who are older than 16 years old. Column 1, column 3, and column 5 show the estimates without control variables while control variables are added in Column 2, column 4, and column 6. Each regression includes survey-year fixed effect, district of birth fixed effect, cohort of birth fixed effects, and province of residence fixed effect. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.14: The effect of the 1997-1998 El Niño on Primary Education Completion: Heterogeneous Effects (by parental education)

Dep. Variable:	Primary Education Completion					
Sample:	Full	Full	Urban	Urban	Rural	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Mother without primary education						
treatment_inutero	0.00675	0.00644	0.0130	0.0124	-0.0164	-0.0170
	(0.00875)	(0.00872)	(0.0117)	(0.0117)	(0.0150)	(0.0150)
Number of observations (N)	38,494	38,494	20,690	20,690	17,804	17,804
Adjusted R^2	0.073	0.076	0.073	0.073	0.080	0.080
Panel B: Mother with primary education						
treatment_inutero	0.00463	0.00464	0.00397	0.00402	0.0456	0.0480
	(0.00337)	(0.00334)	(0.00329)	(0.00326)	(0.0483)	(0.0487)
Number of observations (N)	19,873	19,873	18,446	18,446	1,427	1,427
Adjusted R^2	0.059	0.059	0.059	0.059	0.221	0.222
Panel C: Father without primary education						
treatment_inutero	0.00276	0.00253	0.0109	0.0107	-0.0209	-0.0213
	(0.00868)	(0.00865)	(0.0102)	(0.0102)	(0.0166)	(0.0166)
Number of observations (N)	31,115	31,115	15,147	15,147	15,968	15,968
Adjusted R^2	0.074	0.076	0.074	0.074	0.077	0.077
Panel D: Father with primary education						
treatment_inutero	0.00498	0.00503	0.00471	0.00477	-0.00521	-0.00567
	(0.00855)	(0.00855)	(0.00962)	(0.00962)	(0.0239)	(0.0242)
Number of observations (N)	27,252	27,252	23,989	23,989	3,263	3,263
Adjusted R^2	0.068	0.068	0.070	0.070	0.081	0.082
Cohort of Birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Province of residence FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey year FE	Yes	Yes	Yes	Yes	Yes	Yes
District of birth FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: This table reports the treatment effects estimates on primary education completion for individuals born between 1990-1998 and who are older than 16 years old. Column 1, column 3, and column 5 show the estimates without control variables while control variables are added in Column 2, column 4, and column 6. Standard errors clustered at the district of birth are shown in parentheses. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.15: Effect on students' preference for engineering: including covariates

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

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

Table A.16: The effect of exposure to role models on students' preference for engineering by quartile of math performance: LATE

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

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

Table A.17: Robustness check: high-ability math and science

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

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for engineering, separately by different groups of students based on skills in math (M) and science (S). Estimates correspond to i) Full sample of schools (Panel A), ii) only schools located in main regions (Piura, Tumbes, Lambayeque), Panel B. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) including covariates. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table A.18: Robustness check: average school ECE math scores

Outcome: Prefer Engineering	Control group mean female (1)	Treatment effect (ITT) female (2)	Standard error (3)	Control group mean male (4)	Treatment effect (ITT) male (5)	Standard error (6)	N (7)	Diff (ITT) p-value (8)
All	0.139	0.021	0.016	0.405	0.025	0.025	4504	0.865
Quartile 1	0.076	-0.018	0.017	0.271	0.019	0.035	1434	0.356
Quartile 2	0.138	0.018	0.026	0.403	0.078*	0.044	1539	0.219
Quartile 3	0.194	0.013	0.042	0.546	-0.060	0.068	624	0.303
Quartile 4	0.205	0.097**	0.041	0.554	0.018	0.047	907	0.174
Main Regions								
3 Regions (3R)	0.129	0.032*	0.018	0.396	0.035	0.028	3508	0.938
Quartile 1	0.068	-0.014	0.017	0.251	0.057	0.035	1129	0.093
Quartile 2	0.138	0.036	0.028	0.389	0.078	0.051	1227	0.451
Quartile 3	0.195	0.022	0.045	0.527	-0.009	0.076	493	0.711
Quartile 4	0.175	0.132***	0.042	0.573	-0.029	0.052	659	0.016

Notes: This table reports the intent to treat (ITT) estimates for girls and the ITT for boys on preferences for engineering, separately for different subgroups of students based on self-reported baseline math scores. Column 1 and column 4 show the average value for female and male students in the control group, respectively. Column 2 and column 5 report the intent to treat estimates (ITT) for females and males, respectively. The estimates are obtained from a regression following equation (3.1) and it controls for average school 2015 ECE math scores. p-value for the difference in means test among males and females is reported in column 8. The regression controls for city fixed effects since the randomization was stratified by city. Standard errors clustered at the unit of randomization (school) are reported in column 3 and 6. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.19: The effect on students' preference for engineering: School-UDEP distance, women in the top 25 percentile

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

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

Table A.20: The effect on students' preference for engineering: school-UDEP distance, men in the bottom 25 percentile

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

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

Table A.21: The effect on students' preference for engineering: school-UDEP distance, men

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

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

Table A.22: The effect on students' preference for engineering: school-UDEP distance, women

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

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

Table A.23: The effect on students' preference for engineering: school-UDEP distance, women (continued)

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

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

Table A.24: The effect on students' preference for engineering: school-UDEP distance, men (continued)

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

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

Table A.25: Heterogeneous effects by type of engineering: only girls

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

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

Table A.26: Supply of Academic Programs

Business Administration	Journalism
Law	Mechanical Engineering
Economics	Civil Engineering
Industrial Engineering and Systems	History
Architecture	Administration and Services
Audio- Visual Communication	Medicine
Communication and Marketing	Psychology
Accounting and Internal Auditing	
Early Childhood Education	
Primary Education	
High School Education	

Table A.27: Manipulation test for continuous running variable

Cutoff	Restriction time	BW	p-value
Probationary cutoff of 8	Full sample	2.5	0.56
Probationary cutoff of 8	first term	2.5	0.89
Probationary cutoff of 8	first and second terms	2.5	0.73
Probationary cutoff of 8	first, second, and third terms	2.5	0.64
Probationary cutoff of 8	Full sample	1	0.76
Probationary cutoff of 8	first term	1	0.24
Probationary cutoff of 8	first and second terms	1	0.75
Probationary cutoff of 8	first, second, and third terms	1	0.82
Probationary cutoff of 8	Full sample	0.6	0.98
Probationary cutoff of 8	first term	0.6	0.41
Probationary cutoff of 8	first and second terms	0.6	0.90
Probationary cutoff of 8	first, second, and third terms	0.6	0.96

The null hypothesis is that there is no manipulation around the cutoff. The sample is restricted to students who started the program at the age of 17-23 years old. Cases when the student has to drop-out are excluded.

Appendix B

Survey Instruments

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

Q1. School:

Q2. City:

Q3. Sex: 1. □ male 2. □ female

Q4. Age (In years completed):

Q5. Final course grade on Math in grade 10:

Q6. Final course grade on Language in grade 10:

Q7. Final course grade on Science in grade 10:

☺ If you do not remember exact grades please write an approximation.

☺ Now, we are going to ask easy questions about your career preferences. Remember that there is no correct or incorrect answer. Please respond to the following questions honestly.

Q8. Would you like to study at university after graduating from high school?

(Important: select only one option. If you are still undecided, select the option that comes close to what you would like to do)

1. □ Yes ⟶ (Go to question Q9 and continue the survey if your choice was "Yes")

2. □ No ⟶ (Go to question Q10 and continue the survey if your choice was "No")

Q9. Please write the name of the career you would like to study the most in any university. (If you are in doubt between several careers that you like the same please write the name of one of them)

Q10. Have you already decided at which university to study? (Select the option that applies)

1. □ Yes ⟶ (Go to question Q11 and continue the survey if your choice was "Yes")

2. □ No ⟶ (Go to question Q12 and continue the survey if your choice was "No")

Q11. Please answer questions Q11a, Q11b, and Q11c:

Q11a. Write the name of the university where you have decided to study:

Q11b. Write the name of the career that you are going to study at this university:

Q11c. Are you already enrolled or have you reserved a place in this university? (Select one option only and go to question Q12. Continue the survey)

1. □ Yes 2. □ No

☺ Read carefully each of the following questions, and answer according to your own view. Remember that there is no correct or incorrect answer.

Q12. Imagine that Javier and Lorena are two of your best friends. Both of them have a final course grade in Math and in Science of 20. Javier and Lorena are not sure which career to study. Which field of study would you suggest to each of them?

Field of study that you suggest to Lorena:

Field of study that you suggest to Javier:

Q13. One person studied Informatics Engineering in the best university in Peru. After having worked for more than 10 years in companies such as Microsoft, Facebook, IBM, and Google, this person started his/her own business. His/her company is one of the top five leading engineering companies in the country. In your opinion: (Please select one option only)

1. ◻ Even though this person can be male or female, it is more probable that is male.

2. ◻ Even though this person can be male or female, it is more probable that is female.

Q14. One type of engineering is civil engineering. Please list five other types of engineering: (If you do not remember another five types of Engineering, list the ones you remember and leave the other blanks unfilled)

Q15. One person graduated from the Industrial Engineering program offered by a university in Peru two years ago. Currently, the person is working. How much do you think the person earns per month? (Select one option only)

1. ◻ Less than 1000 soles 3. ◻ Between 2000 and 3000 soles 5. ◻ Between 4000 and 5000 soles

2. ◻ Between 1000 and 2000 soles 4. ◻ Between 3000 and 4000 soles 6. ◻ Between 5000 and 6000 soles

7. ◻ Between 6000 and 7000 soles 8. ◻ Between 7000 and 8000 soles 9. ◻ Between 8000 and 9000 soles

10. ◻ More than 9000 soles

Q16. Do you think you have the capacities and qualities to study Engineering at university? (Select one option only)

1. ◻ Yes, I have them 2. ◻ No, I don't have them 3. ◻ I don't know

☺ Next, we are going to ask you some easy questions about your parents. Please respond the best you can to the following questions:

Q17. Age of your father/ attorney in years completed:

Q18. Is your father/attorney an engineer? (Select the option that applies): 1. ◻ Yes 2. ◻ No

Q19. Please select the level of education of your father/attorney:

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

incomplete

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

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

Q21. Age of your mother in years completed:

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

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

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

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

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

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

Q25. How many siblings do you have in total? | 0 | 1 | 2 | 3 | 4 | 5 | ≥ 6 |

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

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

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

| 0 | 1 | 2 | 3 | 4 | 5 | ≥ 6 |

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

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

| 0 | 1 | 2 | 3 | 4 | 5 | ≥ 6 |

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

$\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q32. How many of your brothers are engineers?

$\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

Q33. How many of your sisters are engineers?

$\boxed{0}$ $\boxed{1}$ $\boxed{2}$ $\boxed{3}$ $\boxed{4}$ $\boxed{5}$ $\boxed{\geq 6}$

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

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

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

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

2. □ No

Q36. Is there a motorcycle in your home? :

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

2. □ No

Q37. Is there a TV in your home? :

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

2. □ No

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

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

2. □ No

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

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

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

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

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

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

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

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

Thank you!