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Academic Aptitude Signals and STEM field participation: A Regression Discontinuity Approach

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Abstract

Gender disparities in STEM field participation at all levels are wide and persistent. In this paper we explore whether external signals about academic aptitude can influence female participation in STEM fields. We analyze 10 years of data on aptitude tests administered by a private university in Peru taken by 3,000 high school students each year. Prior to the test, students are asked to state their (non-binding) preferences over college majors. Admission into majors is determined on the basis of cut-off scores on the exam, which has a math and a verbal component. Using a regression discontinuity design, we find that among students whose preferred major was other than engineering, making the engineering cut-off increases the likelihood of enrolling in engineering by 10-12 percentage points. These effects are driven entirely by female students, and no effect is seen for males. We also find that women with higher scores on the verbal component are less likely to make this switch, reinforcing the idea that external signals about aptitude matter for choice of college majors. These results highlight the importance of external validation in influencing career choices in a context where social norms discourage female participation in STEM fields, and have important policy implications.

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1 Introduction

The participation of women in Science, Technology, Engineering and Mathematics (STEM) continues to be significantly below that of males in the majority of countries, including the developed world (Card and Payne (2017), OECD (2016)). In recent years, this under-representation has increasingly been concentrated in math intensive STEM fields, specifically mathematics and engineering (Kahn and Ginther (2017)). In the United States less than 20% of engineers are women and similar female participation rates in STEM related fields are observed in other regions around the world.[1] This disparity has profound consequences both for women as well as the society at large. First, it significantly contributes to the under-representation of females, both at the top of the income distribution (Ortiz-Ospina and Roser (2018)) and in positions of leadership (AAUW (2016)), and consequently to the gender earnings gap (Beede et al 2011). Second, it has negative consequences towards the development of science, technology and economic growth via the misallocation of talent (Hsieh et al. (2019)). For example, there is evidence showing that diverse teams can perform better than high ability teams at problem solving (Hong and Page, 2004).While several factors have been identified as potential drivers of the observed gender gap in STEM enrollment,[2] a growing body of research points to individual self-selection, which is strongly influenced by stereotypes regarding the inability of girls to succeed in math related fields, as the most critical factor explaining females' decisions to opt-out of STEM career paths, both at the high school and university levels.

In this paper we ask the question: *can external signals about academic aptitude influence the decision to major in a STEM field?*. To answer this, we exploit the unique design of a standardized high school aptitude test, the "Prueba de Aptitud Escolar" or PAE test, implemented by a private university in Peru, Universidad de Piura (UDEP). In particular, we focus on the decisions of high school students to enroll in an engineering major after

[1] In countries such as Chile and Colombia, in the Latin American region, women represent less than 20% of professionals in STEM fields.

[2] Biological factors have also received special attention. However, the emerging consensus is that these factors cannot explain the observed differences in STEM field participation (UNESCO (2017), Ellison and Swanson (2010), Pope and Sydnor (2010), Nollenberger, Rodrıguez-Planas, and Sevilla (2016), Justman and Méndez (2018), Niederle and Vesterlund (2010)). Alternatively, research points to neuroplasticity, the brain's ability to create new connections, as the foundation of learning. Scientists emphasize that children of both sexes who are told that their performance can improve by working hard, through the scientific principles of neuroplasticity, achieve higher test scores (UNESCO (2017)). Other factors identified in the literature include differences in preferences, perceptions and beliefs, as well as in exposure to external factors such as cultural expectations and social norms. For an overview of this literature see (Kahn and Ginther (2017)).

being informed of their PAE test results [3].

The PAE test, taken at the end of the first semester of the final year of high school is a standardized test, with two components - math and verbal. Prior to taking it students are required to state their preferred major. Approximately one month after taking the test, students are informed about scores as well as the all the majors they have qualified for. This is based on a student's (standardized) score relative to fixed cut-offs corresponding to each major. For example, any student who scores more than 600 and 400 standardized points in the PAE math and verbal sections respectively, is informed that she has the necessary academic aptitude to be granted admission into the engineering major. It is important to emphasize that students have the option of enrolling in any program for which they meet the cut-off, independent of their previously stated preferences (or high school GPA). In other words, the students stated major preferences when they registered for PAE are not binding. For those students who finally enroll at this university, we can therefore observe their final program enrollment decisions, and study whether it was influenced by their test performance conditional on their pre-test stated major preferences.

We exploit the cut-off based admission system to set up a regression discontinuity (RD) design around the math threshold required for engineering. The identifying assumption is that all other observable and unobservable characteristics vary smoothly around this threshold and any differences in outcomes must be on account of clearing the cut-off. We refer to passing the threshold as an external signal of academic aptitude. The first main result of this paper is that among students whose initial stated preference is different than engineering, passing the math cutoff increases the likelihood of enrolling in engineering by 10 to 12 percentage points. However, this "switch" is entirely driven by female students, and we find no such effects for boys whose initial preferences were other than engineering. We also find no effects of passing the cutoff for students (female and male) whose initial preference was to major in engineering [4].

Second, we find that these results also mask another important dimension of heterogeneity. Among the set of females who don't prefer engineering, those with higher scores

[3]We focus on engineering since it is the only STEM program offered at this university

[4]This is likely to be the case because the PAE test is not the only mechanism for admission at UDEP and the university offers some other admissions tests throughout the year, as well as alternative non-test based admissions procedures (such as direct admission to students from certified high schools or to students at the top of their high school graduating class). Students who want to major in engineering but don't meet the cutoff can still enroll in engineering through these alternative mechanisms.

on the verbal component of the PAE test are significantly less likely to make the switch into engineering upon clearing the cutoff. This is consistent with previous research which suggests that external signals about math ability relative to verbal skills are an important determinant of STEM field participation (Riegle-Crumb et al. (2012), Wang, Eccles, and Kenney (2013)).

Third, to understand whether the value of these external signals is unique to females or to STEM fields, we conduct a similar exercise for the law major [5]. The law major has a verbal cut-off of 550, the highest among all programs at UDEP. Restricting attention to the set of students whose initial preferences were other than law, we find that passing the law threshold increases enrollment in the program, but here the effect is driven entirely by boys, with no effects on female students.

The different responses to external signals about aptitude we observe among male and female students with specific pre-test STEM preferences are consistent with a social setting with stereotypes regarding the "suitability" of females and males to different majors. There is plenty of evidence which suggests that in Peru engineering is largely seen as a field for males and boys are expected to be engineers, particularly if they perform well in math. Females, on the other hand are discouraged from pursuing STEM fields (Rojas, Guerrero, and Vargas (2016)). In such a context, our results show that an external signal about aptitude can help shape preferences towards STEM fields among female students at the margin, and consequently encourage them to select into engineering. Male students not ex-ante interested in engineering, on the other hand, do not react to such external signals. Given the context, these students don't need external signals to pursue engineering. Rather, they have strong preferences towards some other field and knowing that they have "made the cut" for engineering doesn't change those preferences.

The context in which our study is set poses certain threats to the identification strategy. First, the sample for our main estimations only includes those students who ultimately register for a program at UDEP, and not those who took the PAE test but chose not join UDEP. If passing the threshold systematically affects the decision to join UDEP, our estimates would be biased. However, this turns out to not be the case and we find that among the set of all PAE test takers the probability of enrolling at UDEP varies smoothly around the cutoff. Second, as with any RD design, our results would be biased if there is

[5] In Peru, as well as many other Latin American countries, law is an undergraduate major.

a possibility of manipulating test scores around the cutoff. However, the final scores are standardized (with a mean of 500 and standard deviation of 100), there is no possibility of manipulation in our setting

Our work is closely related to the literature on the importance of stereotypes and beliefs as important underlying factors for observed gender disparities in educational and occupational choices. For example, (Eccles and Jacob, 1986) found that parents' gendered stereotype beliefs play a major role in shaping children's attitudes towards math. Similarly, (Lavy and Sand 2015) found that girls with biased teachers in elementary and middle school take fewer math courses in high school and are less likely to major in STEM fields. These factors can strongly affect beliefs about one's own ability to succeed in STEM fields and strengthen the self-selection bias (Beilock et al. 2009). Recent evidence suggests that beliefs in math ability, rather than ability itself, is what drives STEM choices, and that as females progress through the school system, they tend to underestimate their capacity to perform well in math (Kahn and Ginther (2017)). Moreover, there is also evidence in the literature indicating that girls tend to have lower beliefs about their math ability than boys even in contexts in which they outperform them (UNESCO (2017)). In line with these findings, Card and Payne (2017) show that in Canada female high school students with high math performance tend to select non-STEM courses in their last years of high school, reducing as a result their likelihood to register in STEM majors at college.

Our paper also contributes to the literature on information signals and belief updating among college or senior high school students. Most of this literature uses academic performance measured by GPA, university grades, and specific majors characteristic, such as earnings, as external signal treatments on students preferences or belief updating; and, with very few exceptions, is mostly composed of observational studies (Wiswall and Zafar (2011), Arcidiacono (2004), Zafar (2010)). Several studies in this literature suggest that self-efficacy can be influenced through performance accomplishments and results (Bandura (1978), Shull and Weiner (2002)). External, performance-based, signals about one's own academic aptitude to succeed in math intensive fields may play a critical role in influencing female high school students math self-efficacy, and as result, their self-perceptions and STEM career related decisions. For example Justman and Méndez (2018) finds that female students may require stronger prior math ability related signals to choose male-dominated subjects.

Among the very few quasi-experimental studies on academic aptitude signals, and most closely related ours, are Owen (2010) and Avery et al. (2018). The first uses an RD design to compare students with very similar number grades but different letter grades. It finds that females who get a letter grade of A grade in their principles economics course are more likely to major in this field while no similar response is observed among males. Our results complement these findings, by highlighting the role of such signals in shaping preferences for students at the margin. In addition, we also able to provide evidence of the importance of external signals for male students in certain fields of study. The second paper, which also exploits an RD design, examines the effect of high-school advanced placement (AP) exam scores on students major decisions. Their findings indicate that obtaining a higher integer score in a given exam subject increases the student probability to major in that same subject. Our paper also studies how senior high school students respond to higher scores in a aptitude exam. However, we are able to observe college major preferences prior to taking the exam and hence, can explore career adjustment decisions conditioning on these prior preferences. Our quasi-experimental study also complements a recent body of experimental evidence which aims to influence females self-perception to succeed in STEM field through role models. Breda et al. (2018) for example implement an experiment in French high schools where successful female scientists give classroom talks, to influence high school female perceptions regarding STEM careers. They find positive effects concentrated among females at the right end of the math performance distribution. In a study about female participation in economics in the United States, Porter and Serra (2019) use female professionals who had majored in economics to act as role models for university students. They find that female freshman students randomly exposed to short talks by these role models increase their enrollment in economics majors by approximately 8 percent. We contribute to this literature by exploring the effects of an alternative signal which can influence females self-perceptions in math ability and find that low-cost external signals has the potential to increase female participation in STEM fields.

The rest of the paper is organized as follows. Section 2 discusses the institutional context of our study. In section 3 we discuss our RD design and assess its validity. In section 4 we present our results. Finally, section 5 concludes.

2 Institutional Context

Within Peru, all students in both private and public schools are required to cover the same curriculum during their primary and secondary education (until the end of high school). The curriculum is designed, implemented, and monitored by the Ministry of Education. The official Peruvian high school curriculum does not differentiate between students who aim to pursue STEM and non-STEM college majors.[6] Moreover, Peru does not have a centralized university level admission exam, and each university (both private and public) designs its own admission mechanisms. In general, admission criteria is based on the performance on an entrance exam, and universities do not require a minimum grade in high school math to those who wish apply to STEM related careers.

While STEM fields include a variety of university programs such as Biology, Chemistry, Math, Statistics, Computer Science and Physics, in Peru the most popular STEM program is Engineering. In 2015 and 2016 for example, 91% of the approximately 550,000 students who applied for admission into a STEM major did so in engineering. Engineering also happens to be one of the most male-dominated STEM fields (Kahn and Ginther (2017)); only 29.6%[7] of all individuals who applied to an engineering program in Peru were females.[8]

Universidad de Piura (UDEP) is a Peruvian elite private university which ranks among the top ten higher academic institutions in the country.[9] UDEP main campus is located in the city of Piura, in the northern coast of Peru, and enrolls approximately 6,000 undergraduate students each year across 15 academic program. For STEM programs, UDEP only offers programs in engineering.[10]

On a yearly basis since 1993, UDEP has administered a standardized high school aptitude test (PAE) to more than 3,000 senior high school students in approximately 150 schools, mainly in the northern region of the country. Most of these are private schools attended by students belonging to middle and upper-middle class families. The PAE test

[6]While the educational content does not vary between schools, it is possible that quality of teachers varies by geographic location or school level funding.
[7]This percentage is very close to the one observed in our study sample.
[8]https://www.sunedu.gob.pe/sibe/
[9]Several academic programs at UDEP, such as Mechanical and Electric Engineering, Industrial and System Engineering and Economics, rank among the country's top five.
[10]Specifically civil, mechanical, and industrial.

is administered the second week of August, and the results are available online by the first week of September. The high school year in Peru starts in early March and ends in early December.

The PAE entrance exam is designed by the Faculty of Education at UDEP and administered by the University's Admissions Office. The test is composed of a math and a verbal aptitude sections. The math and verbal scores obtained by students are standardized for each cohort taking the test. The standardized scores are centered at 500 points and have a standard deviation of 100. According to UDEP academic authorities, the test's main objective is to evaluate senior high school students' understanding of key math and verbal concepts at the high school level, as well as to assess whether or not they have the academic aptitude required to perform satisfactorily in the academic programs offered at UDEP.[11]

As an additional benefit, the PAE entrance exam provides students with immediate college admission offers into any major for which their math and verbal standardized scores are above the major specific aptitude thresholds. The required standardized thresholds in all academic programs at UDEP have not varied since the test was first implemented in 1993, and students are fully informed about these thresholds when registering for the test. For example, the necessary threshold for direct admission into an engineering program major is 600 standardized points on the math test and 400 on the verbal test. These are respectively the highest math and lowest verbal thresholds among all academic programs at the university.[12] At the other extreme tail of admission requirements, admission into the law program at UDEP requires a verbal score of 550 points (the highest across all programs) and a math score of 400 points (the lowest across all programs).[13]

When senior high school students register to write the exam around June and early July, they are asked to state their preferred choice of program. However, these stated choices are not binding; after observing their score, students can register into any program for which they pass the required threshold. It is also important to emphasize that the PAE exam is not the only admission mechanism at this university.[14] UDEP also imple-

[11] For more details see http://www.pae.udep.edu.pe/

[12] Less than 5 percent of those who score 600 points or higher in the math section score less than 400 in the verbal one.

[13] Less than 5 percent of those who score 550 or higher in the verbal section score less than 400 on the math test.

[14] It is however considered the hardest one by UDEP admission and academic authorities, as well as the one

ments several regular admission tests in the last quarter of the school year (from October to December), as well as during January and February (the academic year at UDEP starts the last week of March). In addition, direct admission into any academic program is offered to students in the upper third of their class cohort who belong to a school certified by UDEP as a *High Quality Education Center*.[15] Moreover, scholarship decisions are independent of the PAE test results; the assignment of scholarships is based on an independent academic evaluation, which must be taken by all students who are interested in obtaining a scholarship at UDEP.[16] Even in schools where the PAE test is administered, students, while encouraged, are not required to take the test. In our sample, roughly half of the students in schools which are offered the PAE exam do not take it. Finally, for students within the Piura region, the test costs $20 USD for those in private schools, and $12 USD for those in public schools. The test is free for students outside the Piura region.

Given the described context, the PAE exam has the potential to work as a signaling (validation) mechanism for students [17]. When students receive their test results in early September, they may update their beliefs regarding their aptitude across various academic programs, which could potentially influence their final choice of major. For example, a female student who did not list engineering as her preferred program but passed the 600 math threshold, receives a strong signal that she has the mathematical aptitude to pursue an academic career in engineering at UDEP, and may then adjust her final decision accordingly.

We therefore use a regression discontinuity design that exploits the PAE admission thresholds, to analyze how the test results influence students academic and career decisions, conditional on their prior career preferences. In particular, we concentrate our analysis on female students that did not list engineering as their preferred career choice during the test registration process.

that better captures academic aptitude at the high school level.

[15] A relevant fraction of the schools in which the PAE is administered are Certified Schools.

[16] http://udep.edu.pe/postulante/concurso-becas-semibecas/

[17] And perhaps also for parents.

3 Empirical Strategy

We use an RD design that exploits the discontinuity generated by the 600 standardized points PAE math threshold, which determines whether or not the student has the academic math aptitude required by the engineering programs at UDEP [18]. Essentially, we compare students just above and below this cutoff to study the causal effect of a STEM related math aptitude signal on their decision to enroll or not in an engineering program at college. Our main RD specifications is given by equation (1) below:

$$R_{is} = \alpha + \rho T_{is} + f(mathscore_{is}) + \mu_{is} \tag{1}$$

Where R_{is} is a binary variable which indicates whether student i in school s enrolled in an engineering program at UDEP. T_{is} is also a binary variable, indicating whether the student passed the required engineering PAE math threshold; and ρ is henceforth the treatment effect of interest. The term $f(mathscore_{is})$ is the RD polynomial function, which controls for smooth functions of the standardized math score (the running variable) and its interactions with treatment status.

Following Gelman and Imbens (2019), we estimate linear local regressions close to the threshold neighborhood.[19] We consider two main baseline specifications to estimate equation (1) in our paper. The first estimates a linear RD polynomial function and includes all individuals whose math score is within 40 standardized points from the engineering math cut-off. The second also estimates a linear RD polynomial, but includes all individuals located within 54 standardized points from the engineering math threshold. These bandwidths correspond to the coverage error-rate (CER) and the mean squared error (MSE) optimal bandwidths suggested by Calonico, Cattaneo, Farrell, and Titiunik (2017) and have been estimated using their *rdbwselect* command.[20] For the later bandwidth, in addition to

[18] Less that 5% of PAE test takers who pass this threshold obtain less than 400 standardized points in the verbal section, the minimum required to be granted admission into an engineering program. Henceforth, in practice the 600 points math cutoff is the one that determines admission into an engineering program for the majority of individuals around this neighbourhood.

[19] Several recent empirical papers in the economics of education literature follow a similar approach. For example, Zimmerman (2017) estimates local linear regressions with low order RD polynomials to estimate the causal impacts of attending elite business schools in Chile.

[20] To compute these bandwidths, we take as the reference group all individuals who took the PAE test, registered at UDEP and stated prior non-engineering preferences; as they are the main focus of our analysis. We work with the default option in the rdbwselect command, which considers a triangular kernel for band-

a linear RD polynomial, we also consider a quadratic one.

To evaluate the robustness of our results to alternative estimation methods, we also estimate equation (1) using the non-parametric estimation method with robust bias corrected confidence intervals suggested by Calonico, Cattaneo, Farrell, and Titiunik (2017); which is implemented in STATA using their command *rdrobust*. In this case, we also consider both the CER and MSE optimal bandwidths options. In our analysis of individuals who did not list engineering as their preferred program, we also perform a sensitivity analysis that evaluates the robustness of our estimations to a set of bandwidths which are immediately adjacent to those used in our baseline RD specifications.[21]

While the PAE test has been implemented since 1993, we only have access to the test related data for the period 2008-2017. Also importantly, our estimations in this paper are restricted to PAE test-takers who decide to enroll at UDEP, as we can only observe the final choice of majors for these students. This sub-sample of students (5,400 in total) represents approximately 50% of all students who registered at UDEP during the period 2008 to 2017; and approximately 20% of all students who took the PAE test within the same period. Individual engineering preferences in our study sample are very similar to those observed at the national level. For example, during the period 2015 to 2016, 27.5% of students in our sample who listed engineering as their preferred program are female; while at the national level this percentage is about 28.9%. Moreover, while at the national level 19.8% percent of all females college applicants applied to an engineering program during the 2015-2016 period; among female PAE test takers who registered at UDEP, 21.71% percent chose engineering as their preferred option.[22]

A critical concern related to our restricted sample, is that individuals who score 600 points or higher in the PAE math section may be more likely to register at UDEP than those who don't. In such case our empirical analysis would provide biased estimates; as enrolled students just above the math cutoff would likely be systematically different from those just below it. However, as mentioned before, while the PAE offers admission into

width estimation. We adjusted the bandwidth for the clustering of the standard errors at the school level (Calonico, Cattaneo, Farrell, and Titiunik (2017)). We obtain similar results if we instead use the MSE bandwidth, considering a uniform kernel and also adjust the bandwidth estimation for the clustering of the standard errors. In this latter case, the corresponding bandwidth is about 38 standardized math points.

[21] It is also important to mention that our main estimations are robust to the inclusion of control variables such as the student verbal score, test year, and place of residence. These results can be provided under request.

[22] https://www.sunedu.gob.pe/sibe/

any engineering program to those who pass the required 600 math threshold, those who just miss the mark are likely to be offered admission into programs with lower math requirements. Moreover, since PAE is not the only admission mechanism at UDEP, students who did not get admitted into their preferred major through PAE, could still end up at UDEP through several other channels. Also importantly, the PAE test is not used in any way as an input in scholarships related decisions. In this sense, we consider that the 600 math threshold is not likely to critically affect the enrollment decision at UDEP.

In Figure 1a we analyze how the enrollment decision varies at the 600 point threshold among the full sample of PAE test-takers.[23] A we can observe, there is no evidence of a critical jump in enrollment at UDEP at this cut-off (centered at 600). We also perform the same visual analysis for specific sub-groups of PAE takers in Figures 1b to 1e: female students, male students, students who did not list engineering as their preferred choice, and females who did not list engineering as their preferred choice. I all cases there is no discontinuity in university enrollment at the threshold. We have also implemented a set of local estimations to analyze UDEP enrollment at the 600-points for the whole PAE sample as well as for specific subgroups within it. These are shown in Panel A of Table 2, and confirm that there is no evidence of any systematic jump in enrollments at the 600 math threshold.

Now, regarding our study sample, a necessary condition to ensure the validity of our RD analysis is that students should not have perfect control over the running variable. In our context this is likely be the case, as the PAE cutoffs are determined in terms of standardized points; and henceforth, the precise grade-point a student needs to enter into a given program is not precisely known, as it depends on her relative performance within his cohort. Moreover, the test grading and standardization procedure is determined entirely by the of Faculty of Education, which plays no tole in admission procedures. In this sense, admission administrators can hardly manipulate individual results as a function of students prior preferences.

In the absence of perfect control or manipulation, students' pre-treatment characteristics for students in our restricted sample are expected to evolve smoothly across the 600 math threshold. In Figures 2a to 2e we show that this is actually the case for a set of demographic characteristics such as gender, verbal score, test year, region of residence, and

[23] In the graphical analysis we use the 40 threshold estimated discusses earlier in this section. Similar conclusions are obtained if we use the full sample instead. See Figure 1 in the Appendix.

prior preferences for engineering. Similar patterns are observed in Figures 3a to 3e, which focus only on the sub-population of students who did not list engineering as their preferred program of studies. In the first row of panels B and C in Table 2 we implement a set local linear regressions to analyze the effects of passing the engineering math threshold on the variables included in Figures 2a to 2e and 3a to 3e. Reassuringly, we do not find evidence of a statistically significant jump at the 600 point math cut-off.[24] In the second row of panels B and C we implement the CCT estimator for the variables under analysis and find similar results. We have also implemented the McCrary (2008) test for manipulation of the running variable[25] in Figure 4. We first run the test for all students, and then for those students who did not list engineering as their preferred choice. As shown in Figures 4a and 4b, there is no evidence of manipulation around the threshold in both cases.

4 Results

As stated before, in this paper we evaluate whether marginally passing the PAE 600 math threshold influences students decisions to enroll into an engineering program at UDEP. Our main focus is on students with prior non-engineering program preferences, particularly females.

We first analyze the graphical evidence related to our baseline results in Figures 5 to 8.[26] We start our visual analysis with Figure 5a. Here we consider the 40 point bandwidth and include all PAE test takers who registered at UDEP (as only for this group we observe their program enrollment decisions). The x-axis captures the standardized math scores normalized at the 600 points threshold while the y-axis captures the proportion of students who enrolled in engineering. As we can observe, there seems to be a discontinuous jump at the threshold; however, it is not statistically significant. We then separate the group of PAE takers who registered at UDEP in terms of their prior program preferences. Figure 5b analyzes engineering registration among those with prior engineering preferences, while 5b focuses on those whose prior preference is related to a career other than

[24] In all cases we use the 40 threshold estimated discusses earlier in this section. Similar conclusions are obtained if we use the full sample instead. See Figure 2 in the Appendix.

[25] See McCrary, Justin. "Manipulation of the running variable in the regression discontinuity design: A density test." Journal of Econometrics 142.2 (2008): 698-714 for further details.

[26] All results use our sample of PAE test-takers which have stated their initial program preferences and end up enrolling in a program at UDEP.

engineering. Note that the jump at the threshold seems to be higher for students whose prior career preferences are not related to engineering; however the confidence intervals at the right and left of the cutoff in Figure 5c intercept, and therefore the observed jump lacks statistical significance.

In Figure 6 we analyze students with prior non-engineering preferences. Figure 6a focuses on males; while figure 6b focuses on females. As we can see in Figure 6a, there is no evidence of any significant jump at the threshold for males. Figure 6b shows that as we get very close to the cutoff, there seems to be a sizable and statistically significant effect for females. Figures 7a and 7b complement the analysis related to Figure 6. These figures present the raw distribution of the data points capturing students enrollment decisions (where one indicates enrollment in engineering). From the comparison of figures 7a and 7b, we can conclude that, around the math cutoff neighbourhood, the concentration of data points with values equal to one clearly jumps as we move from the left side to the right side of the threshold in the case of females (Figure 7b); while for males this jump is less clear (Figure 7a). In Figure 8, we perform the same exercise as in Figure 6, but considering all data points (that is, we consider the full bandwidth). Note that we reach the same conclusions as in Figure 6: among students with prior preferences for programs not related to engineering, passing the 600 points math cutoff on average seems to affect the decisions to enroll in engineering only among female individuals.

Given the insights from our graphical analysis, we proceed to estimate our baseline RD regressions in Tables 3 to 8. All tables, with the exception of Tables 5b and 5c,[27] have the same structure. Columns I and II in each table estimate our baseline RD specifications: in column I we estimate a linear RD polynomial and include all individuals whose math score is within the 40 points standardized math bandwidth; while in column II we again use a linear RD polynomial, but include individuals within 54 standardized points from the cut-off. Column III uses the same bandwidth as in column II, but estimates a quadratic RD polynomial function. In column IV we show the results corresponding to the non-parametric estimation procedure developed by Calonico, Cattaneo, and Farrell (2018) using a linear robust biased corrected CER optimal bandwidth, which is implemented through the STATA command *rdrobust*. In column V we use the same non-parametric estimator as in column IV, but allow for a linear robust biased corrected MSE

[27] In Tables 5b and 5c we perform a series of robustness and bandwidth sensitivity analysis for the results in Table 5a.

optimal bandwidth. [28]

In Table 3 we focus on the full estimation sample (all PAE takers who registered at UDEP) and explore for heterogenous effects in terms of major preferences. Starting with the full sample, the results in columns I and II suggest that passing the 600 point math threshold increases the probability of registering in an engineering program by approximately 9 to 12 percentage points. These estimates are statistically significant at the 10% and 5% levels respectively. Note that the point estimates corresponding to the estimations in columns III, IV and V are relatively close to those in columns I and II; however, they lack statistical significance. We then analyze students accordingly to their prior study program preferences. As we can observe, the treatment effect estimate for those with prior preferences not related to engineering is around 11 percentage points and is relatively stable across all estimations. Moreover, this effect is always statistically significant, and in most cases at the 5% level. On the other hand, the point estimate for those with prior engineering preferences ranges from 2% to 9%, and it is statistically significant only in column II. Note also that the treatment estimate for those with prior non engineering preferences is higher in absolute size than the estimate for those whose who stated a preference for an engineering program; however, the observed difference is not statistically significant.[29]

In Table 4 we again include all PAE test takers who registered at UDEP, but in this case explore heterogenous effects by gender. The results suggest that the female point estimates are in general (with the exception of column IV) sightly higher than the male ones; however, the observed differences are not statistically significant.

Given the results in Tables 3 and 4, Table 5 centers the analysis on students with prior preferences for academic programs other than engineering; and within this group, explores heterogenous effects related to gender. Table 5a presents our baseline results. As we can observe, girls with prior non-engineering preferences are 14 to 16 percentage points more likely to register into an engineering program if they pass the 600 math PAE threshold. Note that this effect is not only stable across all specifications, but also statistically significant (in most cases at the 5% level). In the case of males, the estimated treatment coefficient is about one third the females one, and it is not statistically significant in any of the specifications in Table 5a. We can also observe that the the difference

[28] As we will observe in Tables 3 to 8, the bandwidths corresponding to the non-parametric estimations in columns IV and V are fully flexible, and they vary as we adjust the sub-sample under analysis.

[29] The p-value for the difference in means test is always higher than 10%.

among the females and males estimates in column I hovers relatively close to the 10% significance level, while the difference in treatment effects corresponding to the estimates in column II is statistically significant (with a p-value for the difference in means test equal to 0.055). The results in Table 5a suggest that, among students with prior non-engineering preferences, a positive external signal related to the individual math aptitude to pursue engineering studies, on average increases the likelihood of enrolling into an engineering program among females, but not males.

To analyze the robustness of our baseline results in columns I and II in Table 5a, in Table 5b we add to our regressions a series of year, district and school fixed effects. We also add the individual verbal score as a control variable in all specifications. As we can observe, the treatment effect among females remains stable and statistically significant, ranging from 14 to 19 percentage points. As it was the case in Table 5a, there is not statistically significant effect for males, and this effect remains on average at about one third of the females one. Note also that the difference in treatment effects among males and females is statistically significant in four of the eight specifications in Table 5b.

To analyze the sensibility of our baseline results to alternative bandwidths, in Table 5c we estimate the linear regression corresponding to column I in Table 5a considering a series of alternative bandwidths which are relatively adjacent to the 40 standardized points one used in our main specification. As we can observed in Table 5c, our point estimates are relatively stable across bandwidths and consistently statistically significant among female test-takers only (at the 1% level across all specifications). Moreover, note that in seven of the eight specifications included in Table 5c, the difference in estimated effects between the female and male students is statistically significant at least at the 10% level. The results in Tables 5b and 5c therefore confirm those previously obtained in Table 5a. In a social context where females are under-represented in math-intensive STEM fields, our evidence strongly suggest that external ability signals can help correct the misallocation of females across STEM and non-STEM programs.

In order to study whether the patterns observed in Table 5a are only present among individuals with prior preferences for non engineering programs, in Table 6 we estimate the effect of passing the 600 math threshold among students for whom engineering was the preferred program of studies. As we can observe, when we consider all individuals within this group, the estimated effect ranges from 2 to 10 percentage points and is only statistically significant in columns II and V. When we study males and females separately, we can observe that the treatment estimate is relatively close in terms of size among across genders. Moreover, the treatment effects is never statistically significant among females, and in terms of size, is about half the effect we found for females in Table 5a. These results suggest that that the math aptitude signal has a relatively weak effect among those with prior engineering preferences, and that it has no differentiated effect among boys and girls within this group. Female students in this group may posses higher levels of math self-efficacy and therefore more likely to consider themselves suitable for a university engineering program. Consequently, if by some degree of chance a female student in this group marginally fails the 600 math cut-off, she is likely to try again and enroll in engineering through other entrance mechanisms offered at UDEP.

4.1 Heterogeneous Effects as a Function of Verbal Aptitude

Table 7 extends our analysis of PAE takers who did not list engineering as their preferred program, and explores additional sources of heterogeneity. In particular, we examine whether test-takers within this group respond differently to the math aptitude signal as a function of their performance in the verbal section of the test, which is more relevant to be granted entrance into programs such as law and communication sciences.[30] We suspect that students will also pay attention to their relative performance, which determines their comparative advantage, and that in their final decisions will weight the received math aptitude signal against other signals of academic performance (i.e. their verbal aptitude).

To test for heterogeneous effects related to verbal performance, Table 7a focuses on individuals with prior non-engineering preferences whose PAE verbal score is below their group median; while Table 7b focuses on individuals within the same preferences group whose verbal score is above the median.[31] The results in Table 7a show that among those students below the PAE median verbal score, females who pass the math threshold are approximately 34 to 37 percentage points more likely to switch into engineering; while for

[30] see Riegle-Crumb et al. (2012) for an interesting discussion on the role of relative performance on STEM decisions

[31] We work with the median verbal score estimated for the 40 standardized points math bandwidth in all regressions in Table 7. This is however very close to the median verbal score among the students in the 54 standardized points math bandwidth. Very similar results are obtained if we consider bandwidth specific median verbal scores for the analysis in each column in Table 7. Also, similar results are obtained if instead of running separate regressions below and above the median verbal score, an interaction between the treatment variable and the verbal score is included in the regressions.

males there is no statistically significant effect.[32] Also, the estimated difference between females and males point estimates is statically significant at least at the 5% level in all RD estimations in Table 7a. In Table 7b we focus on those above the median verbal score. Interestingly, in this case there is a statistically significant effect only among males, but not among females (which point estimate is actually relatively low). That is, males in the non-engineering preference group who obtained a high verbal score, are more likely to end registering in engineering if they pass the required math threshold. The results in Tables 7a and 7b also indicate that the observed difference in treatment effects among females below and above the median verbal score is statistically significant as well as the difference observed for males across both verbal performance groups (in all cases at the 5% significance level).

The results in Table 7 suggests that the findings in Table 5a are primarily driven by females below the median verbal score, as they are more likely to switch to engineering relative to females with high verbal scores. Why do girls with higher verbal scores are less likely to register in engineering after passing the math aptitude threshold required for this program? A higher verbal score is a signal for aptitude in the social sciences, and therefore the math aptitude signal may play a weaker role influencing individual decisions if a strong verbal aptitude signal is also received. Moreover, these girls are also more likely to be offered admission into programs which have relatively higher verbal entrance cutoffs, such as law or communication sciences, and as a result they may be subject to stronger family or friends pressure to register in these programs. This pressure may weaken in the case of girls with low verbal scores, as for them the signal clearly states that they are not strong in terms of their verbal aptitude, and a career in the social sciences may not be a good fit for them.

The results in Table 7 also indicate that while on average there is not a statistically significant effect among boys, there is also a fair degree of heterogeneity, as there seems to be an effect for those with relatively high verbal scores. Interestingly, this effect goes in the opposite direction as the one identified for girls: boys with relatively high verbal scores and prior non-engineering preferences are more likeley to end registering in engineering if they pass the 600 math threshold. These are likely boys who who possess the verbal aptitude for a career in the social sciences and are aware of it, as they stated a prior-preference for a non-engineering program; however, they are being told that they are

[32]Note however that the point estimated coefficient is in this case negative.

eligible for admission into any engineering program at UDEP. This situation may favour a context in which their social circle (family or friends) or the existing social norms exert increasing pressure over them to pursue an engineering major. In this sense, while at first the above result may appear as counterintuitive, it is coherent with a social context in which boys are expected to be engineers, particularly if they are good at math.

In Table 8 we replicate the same empirical exercise as in Table 7, but focus instead on those individuals who listed engineering as their preferred option when they registered for the PAE test. Table 8a focuses on those below the median verbal score, while Table 8b focus on those above. As we can observe, there is no evidence of heterogenous effects neither for females nor males. These results confirm that for those with prior preferences for engineering, the math signal, even when weighted against one's own performance in the verbal section, plays a relatively minor role.

4.2 Career Choice Adjustments for Other Types of Prior Major Preferences

The gender specific patterns related to the effect of external aptitude signals on academic program choice may not be unique to prior preferences related to a career in engineering, but common across a range of major preferences. In other words, males and females may present the same behaviour patterns observed in Tables 3 to 8 independently of the academic program under analysis. To explore for this possibility, in Table 9 we study how students adjust their career choice as a function of their prior preference for law studies. As previously mentioned, the verbal score required for admission into the law program is the highest across all UDEP majors, and it is set as 550 standardized points. The treatment dummy in equation (1) then takes the value of one if the student passed the 550 verbal cutoff; and the corresponding RD polynomial is a function o the individual verbal score (which is the relevant running variable). We estimate a linear regression using the 40 point bandwidth (column I in Table 9a) and also implement the non-parametric estimation proposed by Calonico et al (2017) considering a CER bias corrected bandwidth (column 4). In addition to exploring for heterogenous effects related to gender, we also look for heterogeneous effects as a function of the individual math score (columns II, III, V and VI).

The results in Table 9a suggest that among those with prior non-law preferences, passing the 550 verbal cutoff only influences males; and that this effect is primarily driven by those with relatively low math scores. Moreover, the differences in point estimates across genders in columns II, III and IV is statistically significant at least at the 5% level (in column I the p-value is relatively close to the 10% level). It is important to note that the estimation results in Table 9 provide an opposite gendered pattern than the observed in Tables 5 to 7, and allows us to discard the hypothesis of a common gendered pattern which is independent of academic major prior preferences. Also, note that the results in Table 9 are coherent with a context in which males are expected to be engineers: passing the law verbal threshold makes you more likely to register in law as far as your math score is not too high (in which case you would have received the signal that you are fit for an engineering program at college).

5 Conclusions

We implemented a regression discontinuity design which exploits the major-specific admission thresholds of a high school academic aptitude test implemented by a private university in Northern Peru. A particular feature of the test is that students are required to state their prior major preferences before taking it; but can, after observing their scores, register into any academic program for which they meet the required thresholds.

We find that among students whose preferred field of study was not engineering, meeting the math threshold for engineering admission increases their likelihood of enrolling in an engineering program by 10 to 12 percentage points. Interestingly, within this group, females are significantly more likely than males to adjust their career choices towards engineering in response to the math ability signal provided by the exam. This specific result suggests that while males are more likely to have engineering program preferences aligned with their ability; there may be an under representation of female talent into engineering careers due a lower level of self-efficacy to perform in math intensive fields.

We also find that women with higher verbal test scores are less likely to switch into engineering. While at first glance this suggests that individuals take into account their relative performance in order to make career adjustment decisions (Riegle-Crumb et al. (2012)), it can also be the case that girls with higher verbal scores face higher peer and family pressure to remain in the social sciences. This result may also indicate that females require stronger math ability signals to switch into male-dominated STEM fields (Justman and Méndez (2018)). For the case of males with prior non-engineering preferences, while the average effect is small and not statistically significant, those with relatively high verbal scores are actually more likely to switch to engineering if the pass the 600 math threshold. These are likely boys who are aware of their high verbal aptitude and have therefore strong preferences for the social sciences; but for whom their high PAE math score may open the door to increasing, social or self-imposed, pressure to switch into an engineering program.

We have also analyzed the decisions to enroll into the law program at UDEP, an found a pattern of behaviour that runs in the opposite direction as the one related to engineering choices. In this case, males whose preferred field of study was not law are more likely to switch to this program if they reach the verbal law PAE cutoff; and the effect concentrates among those with low math scores. If you are a boy and you are not good at all at math, then the society can accept you as a lawyer.

Overall, our results confirm that the PAE test provides students with an external signal on their math aptitude which likely influences individual self-efficacy, and as a result, career decisions. The observed results may have long term impacts in terms of lifetime earning potentials and overall social welfare, where women in STEM careers earn on average 33% more than comparable women in non-STEM careers (Beede et al. (2011)). Our RD results are in general coherent with a social environment in which males, particularly those with relatively high math aptitude, are expected to be engineers; while females, particularly those with relatively high verbal aptitude, are generally expected to pursue careers in the social sciences.

In contexts where social norms discourage female participation in STEM fields, these results have important implications for policies aimed at reducing the STEM gender gap. Such policies, according to our findings, must take into account that young male and female individuals react differently to similar academic signals on academic aptitude to pursue a STEM related university degree.

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Table 1: Summary Statistics

	Mean	SD	Obs.	Mean	SD	Obs.
		Girls			**Boys**	
		PAE performance and preferences				
Math PAE Scores	483.27	92.05	13,551	515.82	104.51	14,366
Verbal PAE Scores	502.80	96.70	13,551	497.42	102.89	14,366
Prefer Engineering	0.232	0.422	12,927	0.521	0.499	13,696
Prefer Law	0.149	0.357	12,927	0.080	0.271	13,696
Prefer Business	0.339	0.473	12,927	0.288	0.458	13,696
Prefers Communication Sciences	0.127	0.331	12,927	0.048	0.214	13,696
Prefer Others	0.152	0.359	12,927	0.088	0.283	13,696
Enrolled UDEP	0.196	0.397	13,551	0.196	0.397	14,366
	Field at which the individual enrolled at UDEP					
Enrolled in Engineering	0.228	0.419	2,631	0.502	0.500	2,777
Enrolled in Law	0.155	0.366	2,631	0.094	0.291	2,777
Enrolled in Business	0.331	0.471	2,631	0.257	0.437	2,777
Enrollled in Communications Sciences	0.167	0.375	2,631	0.068	0.252	2,777
Enrolled in Others	0.115	0.319	2,631	0.077	0.267	2,777

Table 2. Pre-Treatment Characteristics as a Function of 600 Math Threshold for Engineering Entrance

	I	II	III	IV	V
Dependent Variable: Registered at UDEP (All Programs)					
Panel A- Registered at UDEP in any program, All PAE Test-Takers 2008-2017					
	Full Sample	**Females**	**Males**	**Non-Eng Preferences**	**Females Non-Eng Preferences**
Linear RD	-0.004	-0.020	0.010	0.003	-0.009
(BW 40)	(0.027)	(0.044)	(0.034)	(0.043)	(0.072)
CCT	-0.001	-0.026	0.020	0.026	0.030
(cerrd BW)	(0.053)	(0.067)	(0.069)	(0.065)	(0.087)
Dependent Variables: Other Student Characteristics)					
Panel B- Student Sample Enrolled at UDEP*					
	Sex (=1 if female)	**PAE Verbal Score**	**Student from Piura**	**Test Year**	**Prefers Engineering**
Linear RD	-0.047	-11.129	0.008	-0.340	0.011
(BW 40)	(0.053)	(7.411)	(0.040)	(0.296)	(0.058)
CCT	-0.068	-6.114	-0.012	-0.349	-0.004
(cerrd BW)	(0.113)	(10.333)	(0.070)	(0.300)	(0.067)
Panel C- Student Sample Enrolled at UDEP, Non-Engineering Initial Preferences					
	Sex (=1 if female)	**PAE Verbal Score**	**Student from Piura**	**Test Year**	**Prefers Engineering**
Linear RD	-0.034	0.402	0.009	-0.524	0.004
(BW 40)	(0.079)	(11.062)	(0.053)	(0.460)	(0.053)
CCT	-0.053	2.181	0.005	-0.661	-0.077
(cerrd BW)	(0.137)	(13.709)	(0.081)	(0.535)	(0.066)

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard errors are clustered at the school level.
The linear RD estimators is from an OLS regressions that includes a binary treatment variable for the 600 math-threshold, and a linear polynomial in the running variable: math score (as well as the interaction between the treatment and the running var).
The CCT estimator implements the local-polynomial-based inference procedures for mean treatment effects in the RD design proposed by Calonico et al (2014, 2017). We use the CER bandwidth adjusting for clusters at the school level.
* Sample is restricted to only include PAE test takers who then enroll in UDEP within the years of 2008 -2017.

Table 3. External Signal Effects on Engineering Enrollment: Heterogeneous Effects by Prior Program Preferences

	I	II	III	IV	V
Dependent Variable: Registered in Engineering at UDEP					
	Linear BW 40	**Linear BW 54**	**Quadratic BW 54**	**Linear BW CER**	**Linear BW MSE**
All Test Takers	0.092*	0.122**	0.076	0.090	0.104
	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)
N	1450	1901	1901	1435	1877
Students with Prior Engineering Preference	0.059	0.099**	0.021	0.059	0.068
	(0.05)	(0.04)	(0.06)	(0.06)	(0.05)
N	712	927	927	623	902
Students with Prior Non-Engineering Preferences	0.106**	0.113***	0.117**	0.115*	0.115**
	(0.04)	(0.03)	(0.05)	(0.06)	(0.05)
N	738	974	974	687	996
P-Value Test* (Eng - Non-Eng)	0.41	0.77	0.16	0.48	0.19

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I - III.
Robust bias corrected standard errors are produced in columns IV - V following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP
* P-Value Test: Difference of effect for students with prior engineering preferences - students with prior non-STEM preferences.

Table 4. External Signal Effects on Engineering Enrollment: Heterogeneous Effects by Gender

	I	II	III	IV	V
Dependent Variable: Registered in Engineering at UDEP					
	Linear BW 40	**Linear BW 54**	**Quadratic BW 54**	**Linear BW CER**	**Linear BW MSE**
All Test Takers	0.092*	0.122**	0.076	0.090	0.104
	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)
N	1450	1901	1901	1435	1877
Female Test Takers	0.105	0.138**	0.081	0.054	0.101
	(0.07)	(0.06)	(0.10)	(0.10)	(0.09)
N	654	845	528	334	754
Male Test Takers	0.065	0.106*	0.035	0.079	0.080
	(0.07)	(0.06)	(0.09)	(0.08)	(0.07)
N	796	1056	1056	730	1056
P-Value Test (Females - Males)	0.68	0.77	0.67	0.42	0.22

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I- III.
Robust bias corrected standard errors are produced in columns IV - V following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP.

Table 5. External Signal Effects on Engineering Enrollment Among Students with Initial Non-Engineering Preferences

5a. Heterogeneous Effects by Gender

	I	II	III	IV	V
Dependent Variable: Registered in Engineering at UDEP					
	Linear BW 40	**Linear BW 54**	**Quadratic BW 54**	**Linear BW CER**	**Linear BW MSE**
All Test Takers Non-Engineering Preference	0.106*** (0.04)	0.113*** (0.03)	0.117** (0.05)	0.113** (0.05)	0.115** (0.05)
N	738	974	974	788	1015
Female Test Takers Non-Engineering Preference	0.152*** (0.05)	0.164*** (0.05)	0.143** (0.07)	0.147* (0.08)	0.157** (0.07)
N	431	567	567	426	407
Male Test Takers Non-Engineering Preference	0.045 (0.06)	0.048 (0.05)	0.074 (0.08)	0.065 (0.08)	0.057 (0.07)
N	307	407	407	321	445
P-Value Test (Females - Males)	0.12	0.055**	0.38	0.38	0.19

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I- III.
Robust bias corrected standard errors are produced in columns IV - V following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP

5b. Heterogeneous Effects by Gender, Adding Controls and Fixed Effects

	I	II	III	IV	V	VI	VII	VII
	Dependent Variable: Registered in Engineering at UDEP							
	Linear BW 40	**Linear BW 40**	**Linear BW 54**	**Linear BW 54**	**Linear BW 40**	**Linear BW 40**	**Linear BW 54**	**Linear BW 54**
Female Test Takers Non-Engineering Preferences	0.166***	0.180***	0.181***	0.187***	0.141**	0.166**	0.173***	0.193***
	(0.053)	(0.055)	(0.042)	(0.043)	(0.058)	(0.062)	(0.045)	(0.047)
Male Test Takers Non-Engineering Preferences	0.031	0.061	0.053	0.067	0.048	0.079	0.051	0.073
	(0.063)	(0.059)	(0.051)	(0.046)	(0.066)	(0.066)	(0.053)	(0.051)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
District FE	YES	YES	YES	YES	NO	NO	NO	NO
Sex Specific Year and District FE	NO	YES	NO	YES	NO	NO	NO	NO
School FE	NO	NO	NO	NO	YES	YES	YES	YES
Sex Specific Year and school FE	NO	NO	NO	NO	NO	YES	NO	YES
P-Value Test (Females - Males)	0.100*	0.143	0.060*	0.069*	0.298	0.355	0.089*	0.103
N Females	431	431	567	657	431	431	567	567
N Males	307	307	407	407	307	307	407	407

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP

5c. Heterogeneous Effects by Gender, Alternative Bandwidths around the 40 Point BW

	I	II	III	IV	V	VI	VII
Dependent Variable: Registered in Engineering at UDEP							
	BW 37	**BW 38**	**BW 39**	**BW 40**	**BW 41**	**BW 42**	**BW 43**
All Test Takers	0.114***	0.109***	0.108***	0.106***	0.108***	0.112***	0.118***
Non-Engineering Preferences	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Female Test Takers	0.167***	0.168***	0.165***	0.152***	0.155***	0.162***	0.171***
Non-Engineering Preferences	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Male Test Takers	0.043	0.034	0.034	0.045	0.043	0.044	0.044
Non-Engineering Preferences	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
P-Value Test (Female - Male)	0.056**	0.038**	0.043**	0.12	0.097*	0.069*	0.05**
N Females	402	404	423	431	442	452	460
N Males	282	289	302	307	315	318	328

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP

Table 6. External Signal Effects on Engineering Enrollment Among Students with Initial Engineering Preferences: Heterogeneous Effects by Gender

	I	II	III	IV	V
Dependent Variable: Registered in Engineering at UDEP					
	Linear BW 40	**Linear BW 54**	**Quadratic BW 54**	**Linear BW CER**	**Linear BW MSE**
All Test Takers Engineering preferences	0.059 (0.039)	0.099*** (0.037)	0.021 (0.046)	0.061 (0.046)	0.075* (0.047)
N	712	927	927	762	964
Female Test Takers Engineering preferences	0.061 (0.087)	0.113 (0.079)	-0.022 (0.121)	0.032 (0.101)	0.085 (0.094)
N	223	278	278	243	319
Male Test Takers Engineering preferences	0.056 (0.059)	0.093* (0.051)	0.035 (0.076)	0.083 (0.067)	0.070 (0.062)
N	489	649	649	407	597
P-Value Test (Female - Male)	0.96	0.79	0.65	0.28	0.27

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I- III.
Robust bias corrected standard errors are produced in columns IV - V following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP

Table 7. External Signal Effects on Engineering Enrollment Among Students with Initial Non-Engineering Preferences

7a. Heterogeneous Effects by Verbal Score, Individuals Below Median Verbal Score

	I	II	III	IV	V
Dependent Variable: Registered in Engineering at UDEP					
	Linear BW 40	**Linear BW 54**	**Quadratic BW 54**	**Linear BW CER**	**Linear BW MSE**
All Test Takers	0.143*	0.162**	0.139	0.139	0.151*
Non-Engineering preferences	(0.074)	(0.070)	(0.094)	(0.095)	(0.089)
N	365	494	494	464	466
Female Test Takers	0.374***	0.358***	0.370***	0.346**	0.365***
Non-Engineering preferences	(0.090)	(0.076)	(0.116)	(0.177)	(0.165)
N	198	264	264	170	240
Male Test Takers	-0.097	-0.033	-0.107	-0.236*	-0.159
Non-Engineering preferences	(0.100)	(0.082)	(0.125)	(0.126)	(0.115)
N	167	230	230	73	103
P-Value Test (Females - Males)	0.0003***	.0006***	0.0047***	0.02**	0.007***

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I- III.
Robust bias corrected standard errors are produced in columns IV - V following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP

7b. Heterogeneous Effects by Verbal Score, Individuals Above Median Verbal Score

	I	II	III	IV	V
	Dependent Variable: Registered in Engineering at UDEP				
	Linear BW 40	**Linear BW 54**	**Quadratic BW 54**	**Linear BW CER**	**Linear BW MSE**
All Test Takers	0.071	0.079**	0.097	0.098	0.090
Non-Engineering preferences	(0.047)	(0.040)	(0.064)	(0.068)	(0.065)
N	373	480	480	352	442
Female Test Takers	0.023	0.047	0.024	0.035	0.042
Non-Engineering preferences	(0.069)	(0.057)	(0.085)	(0.084)	(0.078)
N	233	303	303	271	359
Male Test Takers	0.148**	0.140**	0.205*	0.223*	0.185
Non-Engineering preferences	(0.073)	(0.070)	(0.107)	(0.122)	(0.117)
N	140	177	177	125	173
P-Value Test (Female - Male)	0.17	0.23	0.15	0.009***	0.135
P-Value Test[1] (Females A - Females B)	0.016**	0.018**	0.058**	0.237	0.07**
P-Value Test[2] (Males A - Males B)	0.003***	0.015**	0.059**	0.049**	0.01***

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I- III.
Robust bias corrected standard errors are produced in columns IV - V following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP
[1]: This provides a p-value test of the 600 math cut-off on engineering enrollment for below-median verbal score females - above-median verbal score females
[2]: This provides a p-value test of the 600 math cut-off on engineering enrollment for below-median verbal score males - above-median verbal score males

Table 8. External Signal Effects in Among Students with Initial Engineering Preferences

8a. Heterogeneous Effects by Verbal Score, Individuals Below Median Verbal Score

	I	II	III	IV	V
	Dependent Variable: Registered in Engineering at UDEP				
	Linear BW 40	**Linear BW 54**	**Quadratic BW 54**	**Linear BW CER**	**Linear BW MSE**
All Test Takers	-0.008	0.052	-0.050	-0.001	0.024
Engineering Preferences	(0.065)	(0.055)	(0.087)	(0.067)	(0.064)
N	355	455	455	398	500
Female Test Takers	-0.049	0.040	-0.131	-0.067	-0.060
Engineering Preferences	(0.121)	(0.104)	(0.167)	(0.221)	(0.203)
N	98	118	118	77	101
Male Test Takers	0.007	0.061	-0.028	0.016	0.040
Engineering Preferences	(0.073)	(0.063)	(0.093)	(0.079)	(0.073)
N	257	337	337	293	391
P-Value Test (Females - Males)	0.73	0.88	0.66	0.54	0.44

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I- III.
Robust bias corrected standard errors are produced in columns IV - V following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP

8b. Heterogeneous Effects by Verbal Score, Individuals Above Median Verbal Score

	I	II	III	IV	V
	Dependent Variable: Registered in Engineering at UDEP				
	Linear BW 40	**Linear BW 54**	**Quadratic BW 54**	**Linear BW CER**	**Linear BW MSE**
All Test Takers Engineering Preferences	0.112 (0.079)	0.127* (0.071)	0.087 (0.094)	0.100 (0.096)	0.117 (0.093)
N	357	472	472	274	367
Female Test Takers Engineering Preferences	0.121 (0.121)	0.161 (0.111)	0.031 (0.166)	0.016 (0.135)	0.068 (0.123)
N	125	160	160	101	132
Male Test Takers Engineering Preferences	0.101 (0.095)	0.108 (0.082)	0.119 (0.126)	0.163 (0.102)	0.145 (0.102)
N	232	312	312	172	251
P-Value Test (Females - Males)	0.87	0.66	0.61	0.80	0.51
P-Value Test[1] (Females A - Females B)	0.38	0.52	0.50	0.75	0.89
P-Value Test[2] (Males A - Males B)	0.51	0.67	0.46	0.53	0.26

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I- III.
Robust bias corrected standard errors are produced in columns IV - V following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in an engineering program at UDEP
[1]: This provides a p-value test of the 600 math cut-off on engineering enrollment for below-median verbal score females - above-median verbal score females
[2]: This provides a p-value test of the 600 math cut-off on engineering enrollment for below-median verbal score males - above-median verbal score males

Table 9. External Signal Effects on Law Enrollment: Heterogeneous Effects by Law Preferences and PAE Math Score

9a. Test Takers who Do Not Prefer Law

	I	II	III	IV	V	VI
	Dependent Variable: Registered in Law at UDEP					
	All	**Below Median Math**	**Above Median Math**	**All**	**Below Median Math**	**Above Median Math**
	Linear BW 40	Linear **BW 40**	**Linear BW 40**	**Linear BW CER**	Linear **BW CER**	**Linear BW CER**
All Test Takers Non-Law preference	0.075*** (0.019)	0.129*** (0.040)	0.019* (0.010)	0.067*** (0.018)	0.123*** (0.037)	0.013 (0.008)
Female Test Takers Non-Law preference	0.044 (0.027)	0.051 (0.040)	0.024 (0.025)	0.035 (0.028)	0.035 (0.045)	0.013 (0.020)
Male Test Takers Non-Law preference	0.104*** (0.028)	0.249*** (0.063)	0.016 (0.018)	0.091*** (0.026)	0.231*** (0.075)	0.005 (0.006)
P-Value Test (Females - Males)	0.11	0.01***	0.69	0.063**	0.005***	0.613
N Females	774	472	302	908	458	189
N Males	839	337	502	964	388	429

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I- III.
Robust bias corrected standard errors are produced in columns IV - VI following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in the law program at UDEP

9b. Test Takers who Prefer Law

	I	II	III	IV	V	VI
	Dependent Variable: Registered in Law at UDEP					
	All	**Below Median Math**	**Above Median Math**	**All**	**Below Median Math**	**Above Median Math**
	Linear BW 40	Linear **BW 40**	**Linear BW 40**	**Linear BW CER**	Linear **BW CER**	**Linear BW CER**
All Test Takers Prefers Law	0.253** (0.102)	0.239* (0.132)	0.252* (0.13)	0.311*** (0.118)	0.293** (0.126)	0.329 (0.265)
Female Test Takers Prefers Law	0.269** (0.121)	0.276* (0.161)	0.243 (0.188)	0.492*** (0.180)	0.426* (0.225)	0.279 (0.332)
Male Test Takers Prefers Law	0.282 (0.213)	0.142 (0.469)	0.283 (0.212)	0.255 (0.186)	0.115 (0.548)	0.251 (0.359)
P-Value Test (Females - Males)	0.95	0.75	0.89	0.36	0.73	0.50
N Females	154	87	67	119	89	60
N Males	72	28	44	116	32	39

As it is standard, ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Standard error clusters are at the school level for columns I- III.
Robust bias corrected standard errors are produced in columns IV - VI following the work of Calonico et al. (2017) to produce inference-optimal bandwidth choices corresponding to the corresponding sub-sample of analysis. This is calculated using the rdrobust command in Stata.
Dependent Variable- a dummy variable equal to one if the PAE test taker enrolls in the law program at UDEP

6 Figures

Figure 1. Student Enrollment as a Function of Math Score, Engineering Cut-Off (BW 40)

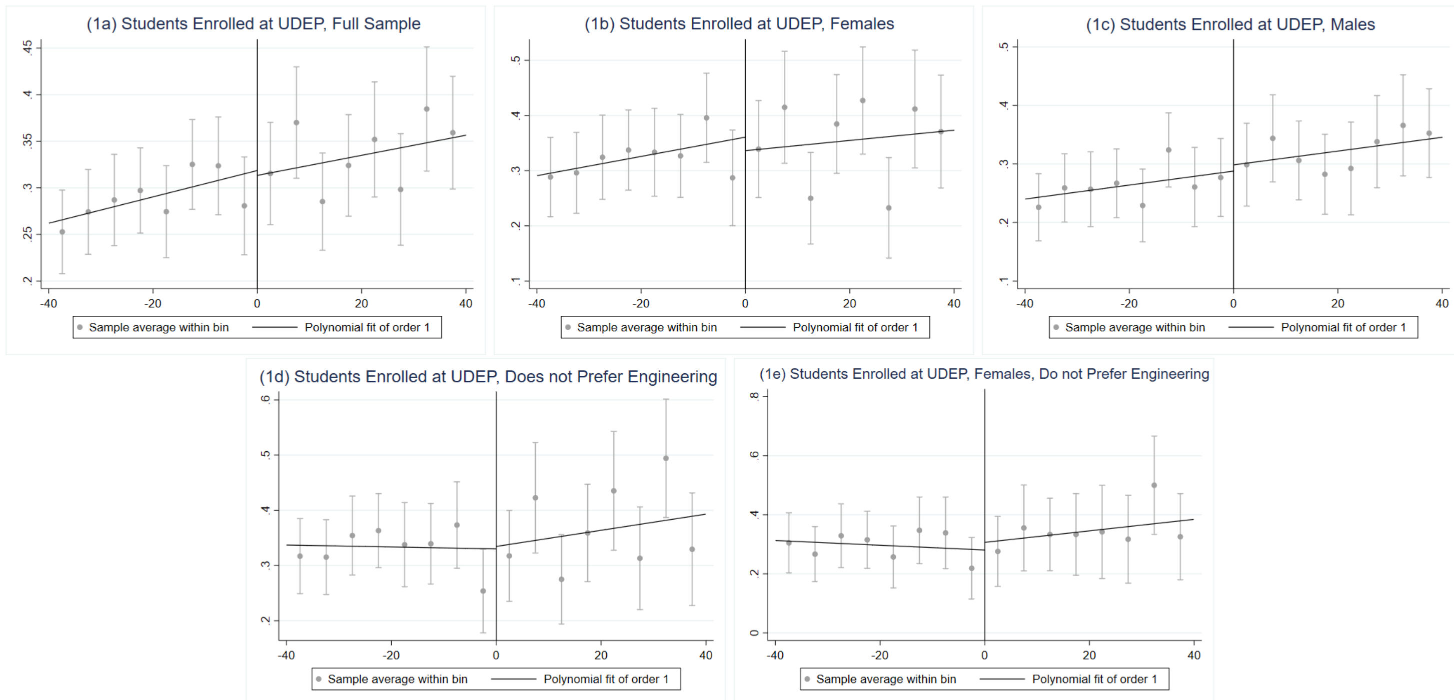


Figure 2. Pre-Treatment Characteristics at 600 Math Threshold, Students Enrolled at UDEP who took PAE (BW 40)

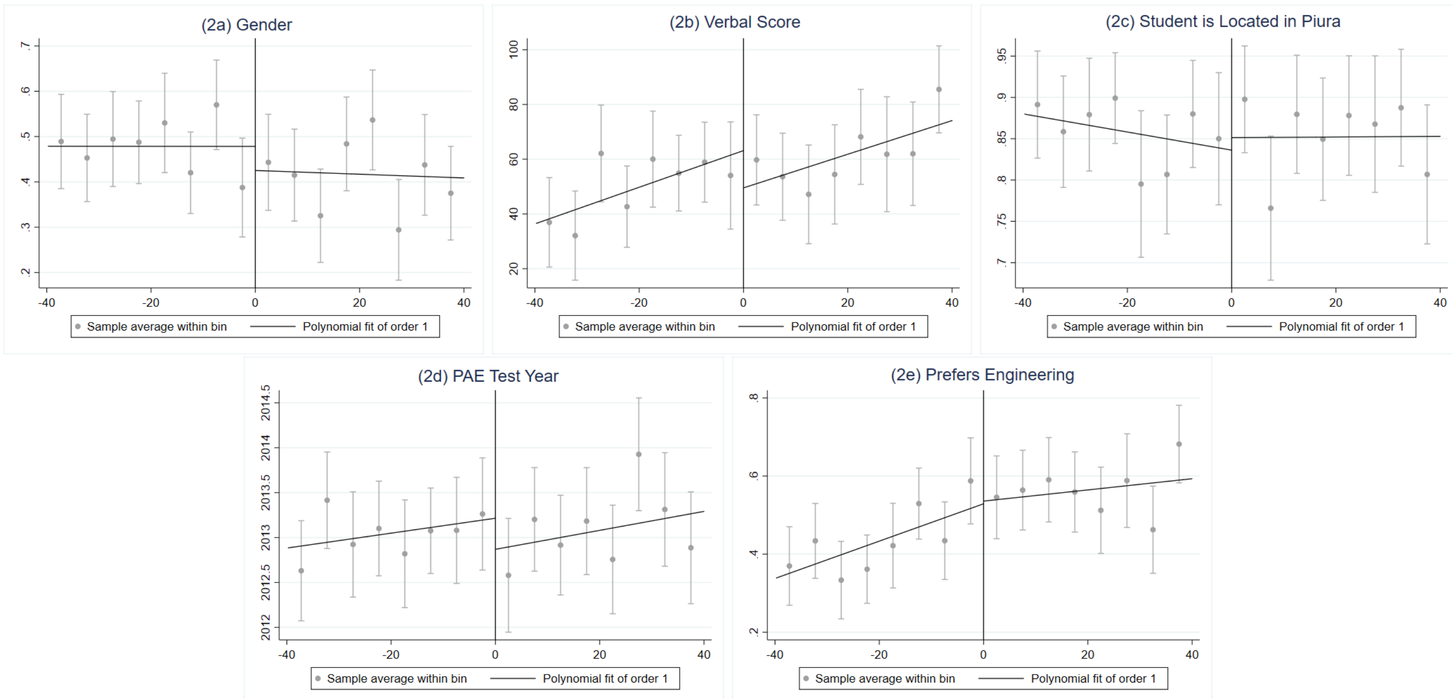


Figure 3. Pre-Treatment Characteristics at 600 Math Threshold, Students Enrolled at UDEP who Don't Prefer Engineering (BW 40)

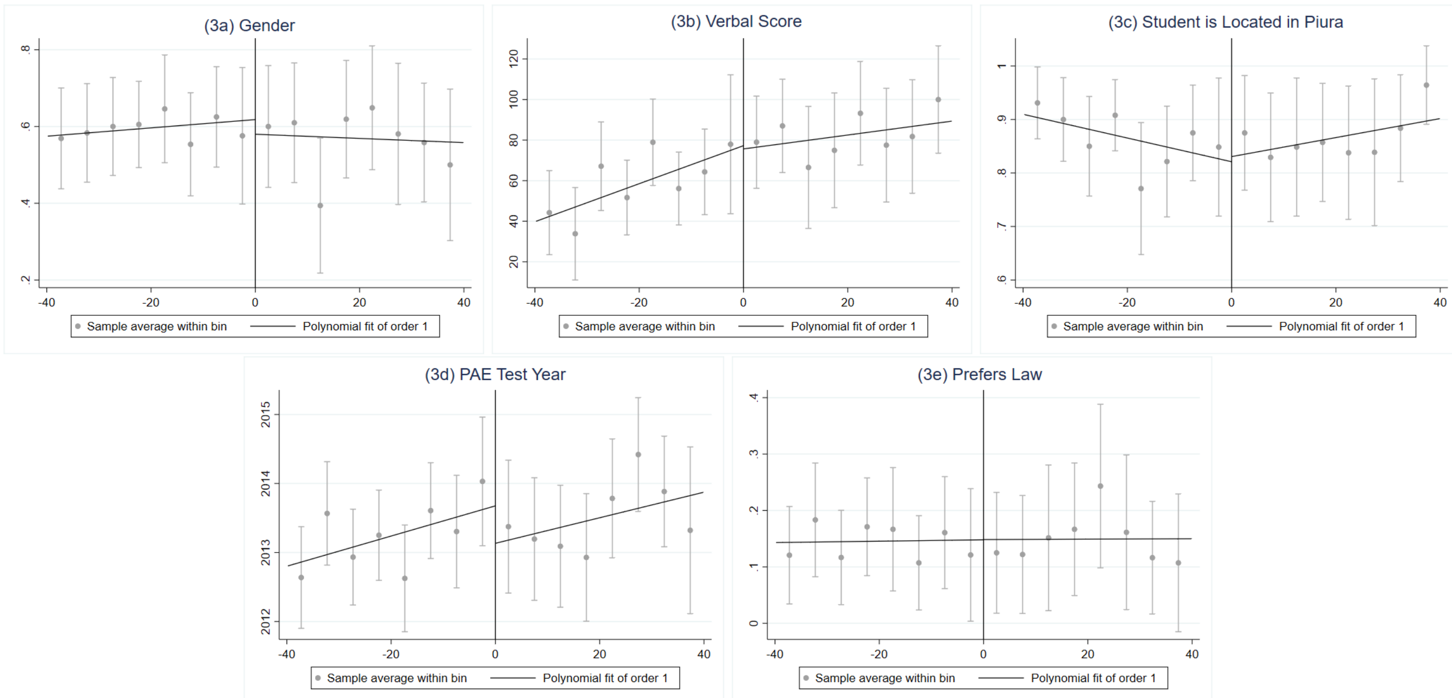


Figure 4. McCrary Density Test of Running Variable (PAE Math Test Score)

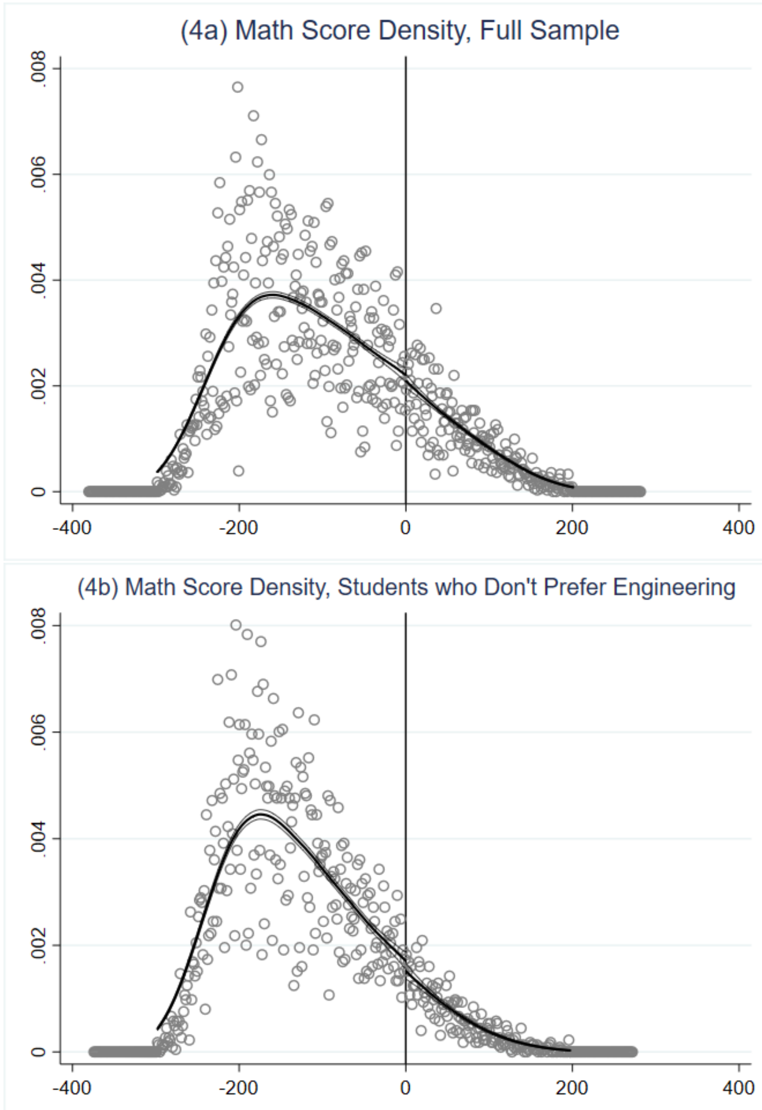


Figure 5. External Signal Effect of Reaching the Engineering Math Threshold on Engineering Enrollment Decisions (BW 40)

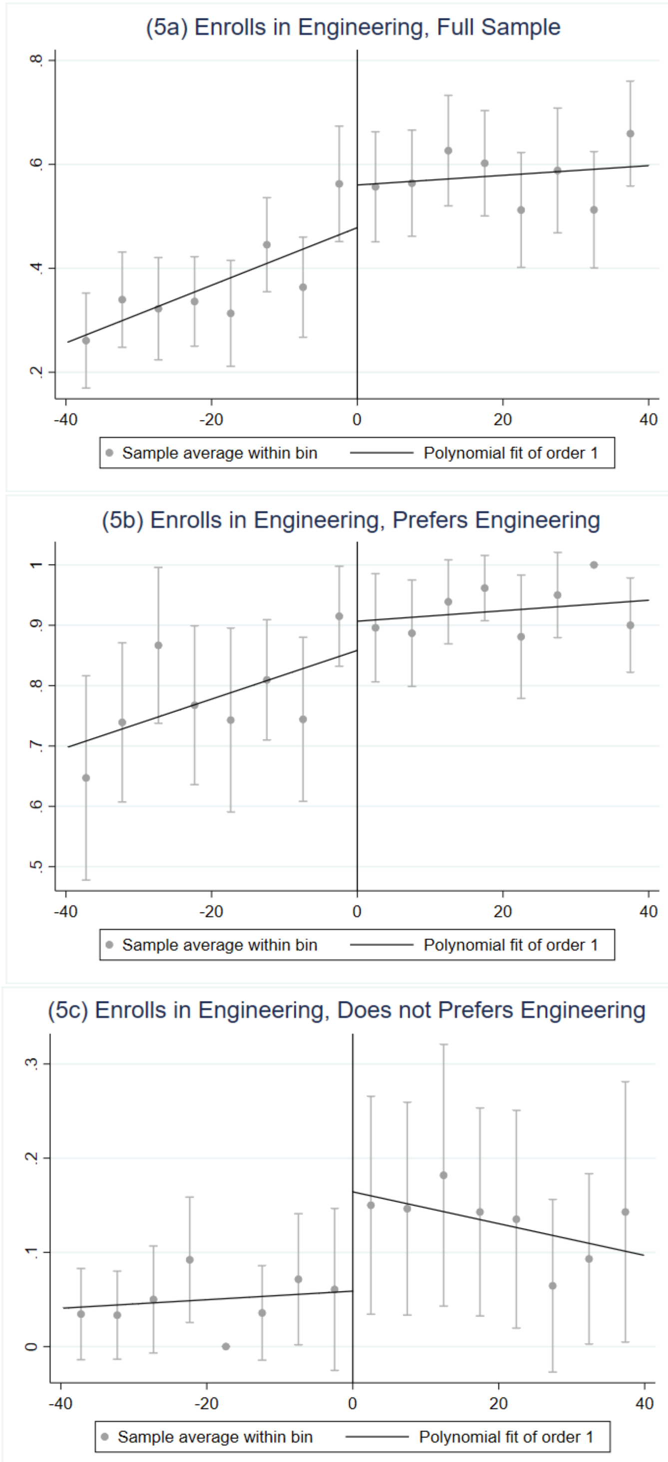


Figure 6. External Signal Effect of Reaching the Engineering Math Threshold on Engineering Enrollment, Heterogeneous Effects by Gender (BW 40)

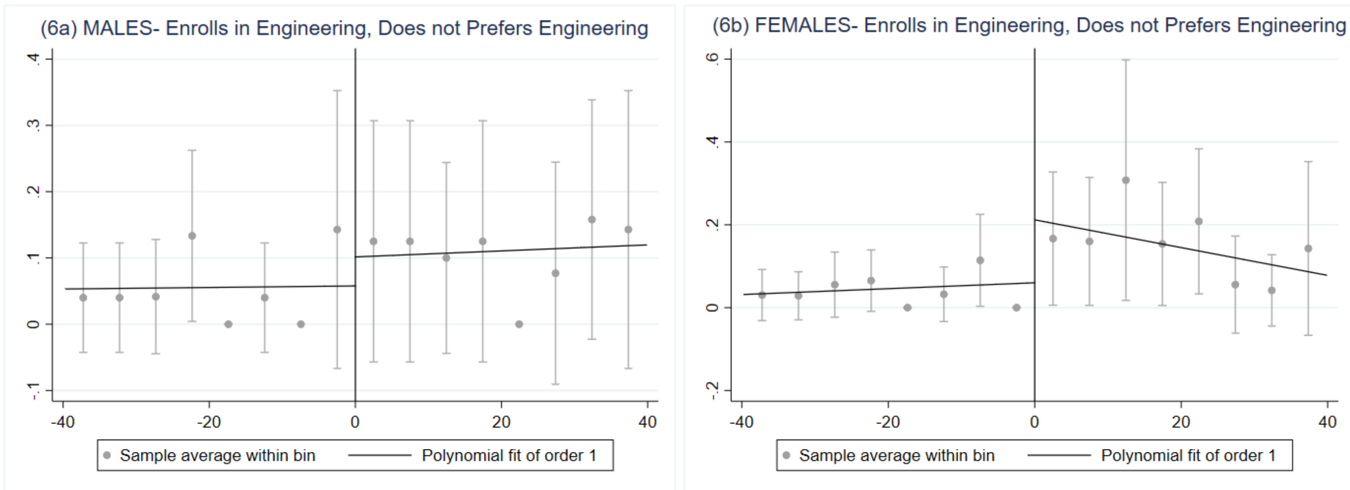


Figure 7. Scatter Plot of Engineering Enrollment, by Gender (BW 40)

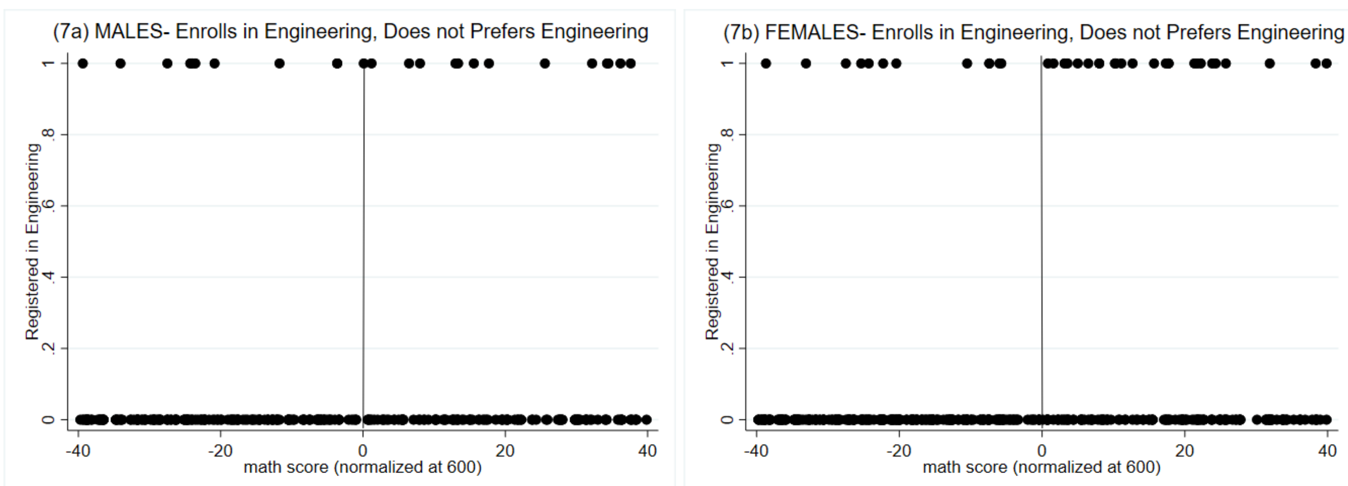
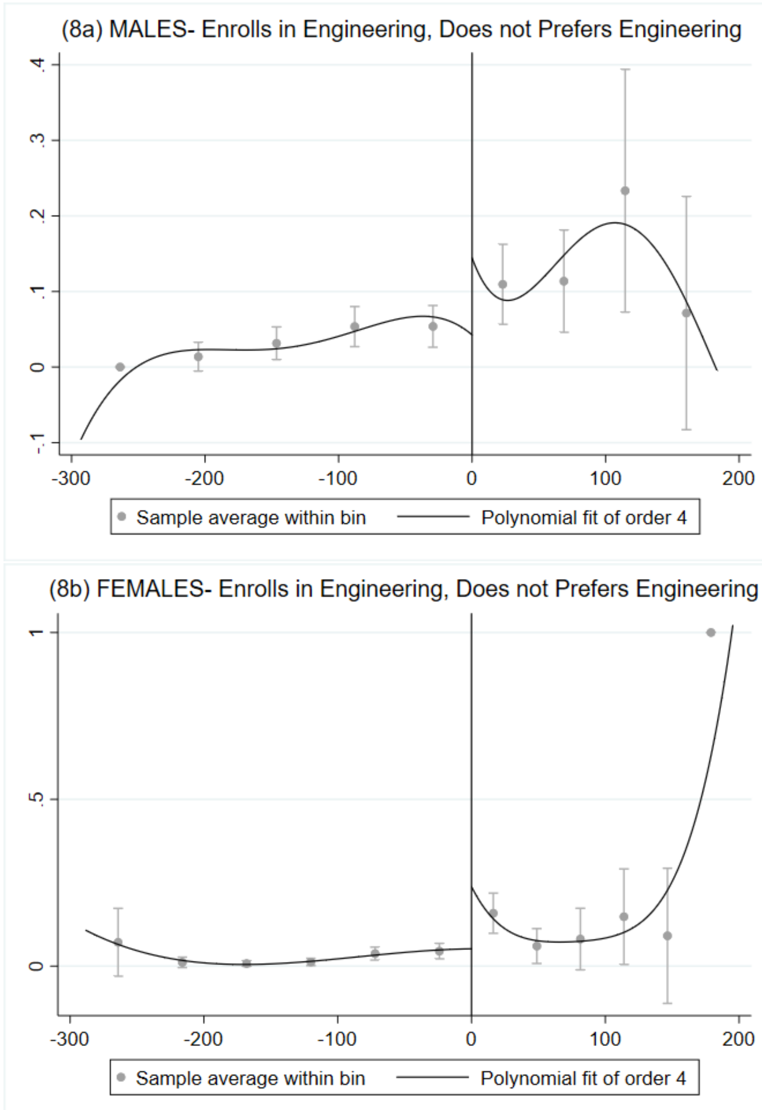
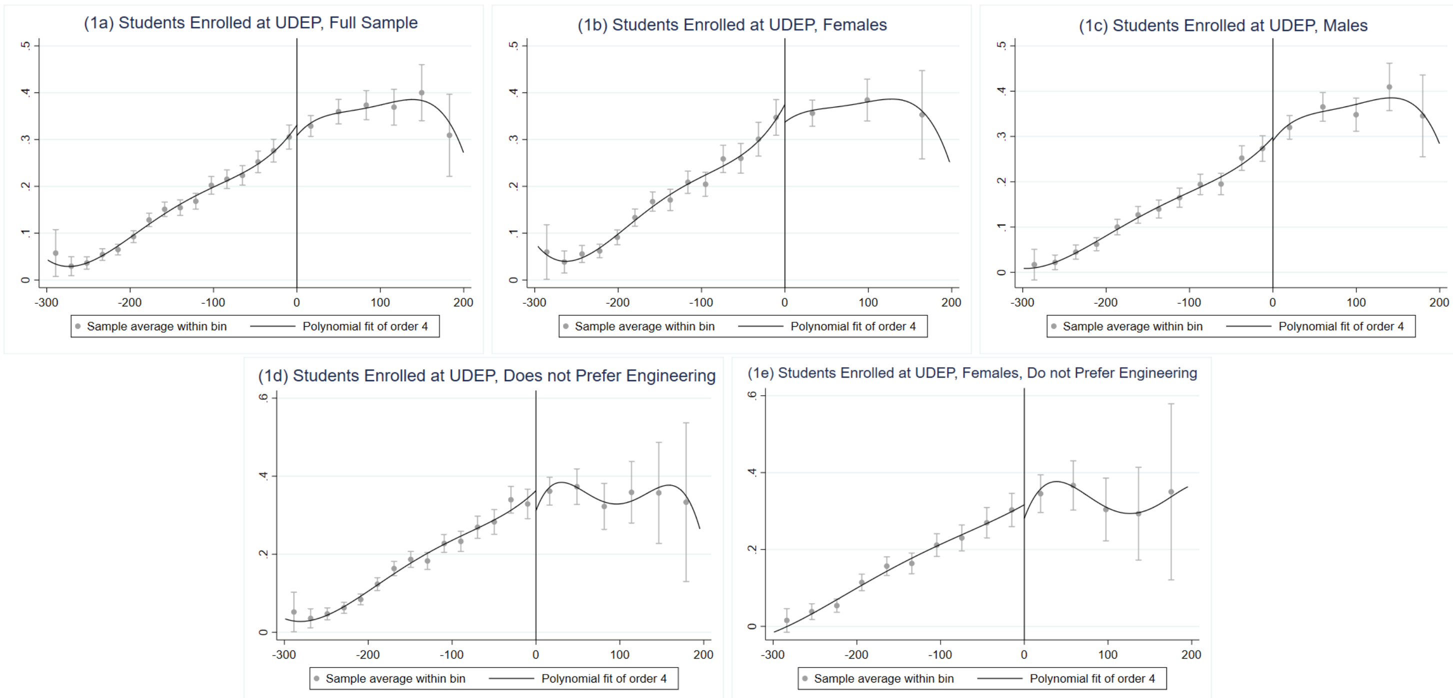


Figure 8. External Signal Effects of Reaching the Engineering Math Threshold on Engineering Enrollment, Heterogeneous Effects by Gender (Full BW)

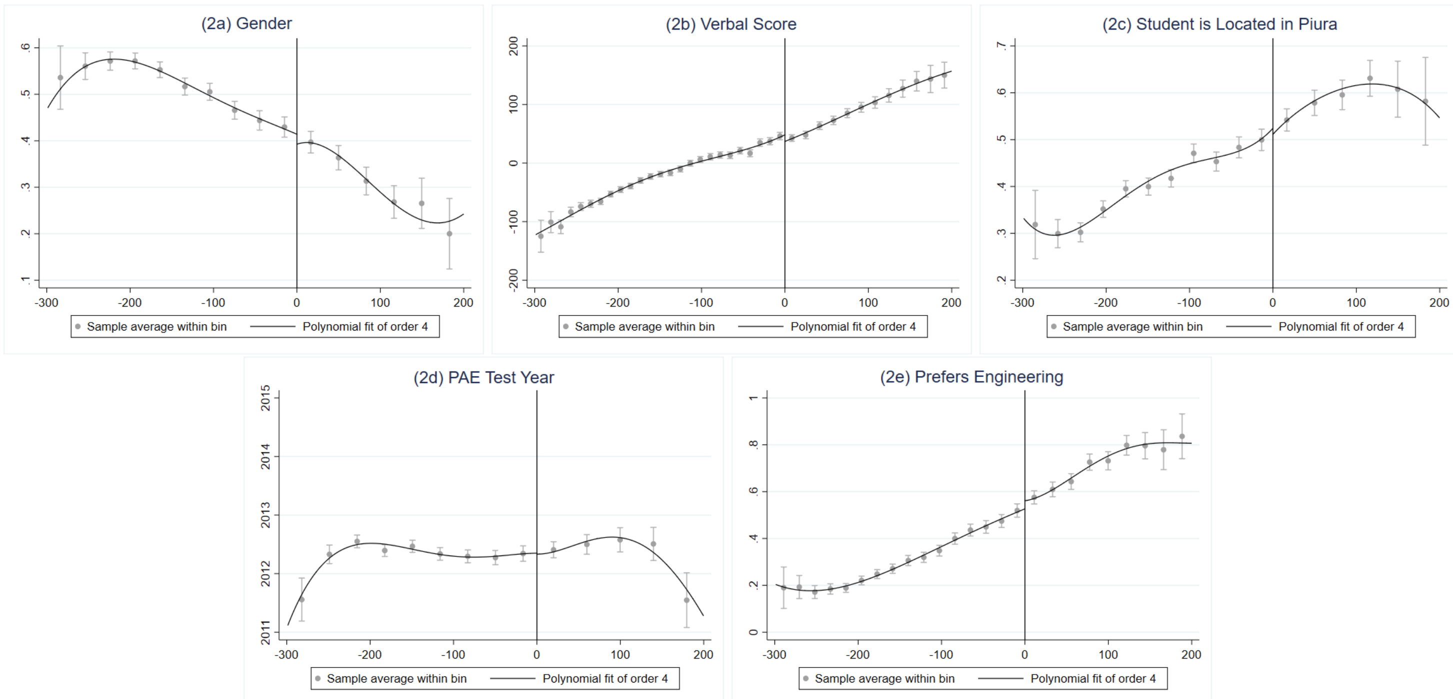


7 Appendix

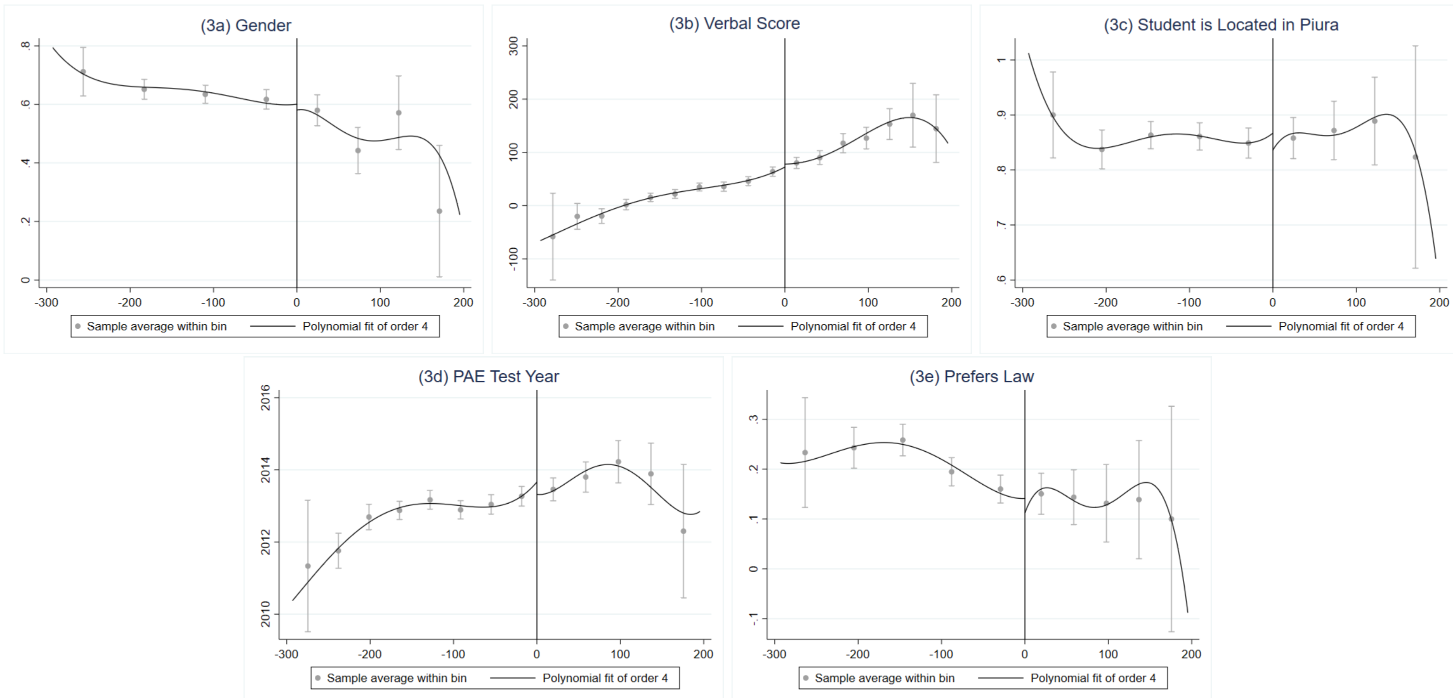
Appendix Figure 1. Student Enrollment as a Function of Math Score, Engineering Cut-Off (Full BW)



Appendix Figure 2. Pre-Treatment Characteristics at 600 Math Threshold, Students Enrolled at UDEP who took PAE (Full BW)



Appendix Figure 3. Pre-Treatment Characteristics at 600 Math Threshold, Students Enrolled at UDEP who Don't Prefer Engineering (Full BW)



Appendix Figure 4. External Signal Effect of Reaching the Engineering Math Threshold on Engineering Enrollment (Full BW)