# Joining the Men's Club: The Returns to Pursuing High-earnings Male-dominated Fields for Women*

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**Abstract**. The low participation of women in high-earnings fields such as technology and engineering (TE) is believed to contribute to the gender wage gap. This paper investigates the labor market returns to pursuing majors in TE for men and women using data from Chile. We link administrative records on postsecondary application and enrollment to labor earnings and fertility data, and exploit discontinuities in admission generated by Chile's centralized system of admission to higher education. We find that enrollment in TE as opposed to humanities, arts or social science (HASS) increases men's earnings and employment by 74% and 29%, but does not increase earnings or employment for women. The absence of returns for women seems to be the consequence of them failing to fully integrate into *the men's club:* enrollment in TE increases the probability of employment at high-paying and male-dominated industries for men, but not for women. Finally, we show that enrollment into TE does not affect women's fertility or their partners' test scores and earnings.

*Keywords:* Gender, College Choice, Chile

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# 1 Introduction

The low participation of women in STEM fields has long been a matter of concern for researchers and policy makers. In the United States, 19.2% of B.A. holders with a degree in technology or engineering are women.[1] In Chile, the focus of our paper, women represented 22% of first year enrollees in these fields in 2005. The underrepresentation of women in these fields is seen as problematic in part because it prevents women from contributing to science and innovation, but also because it is believed to contribute to the gender wage gap. Some STEM fields such as technology and engineering tend to pay particularly high wages to both men and women. In fact, a number of papers have documented that differences in men and women's choices of college major (Sloane et al., 2019), occupation, and industry (Blau and Kahn, 2017; Groshen, 1991; Macpherson and Hirsch, 1995; Altonji and Blank, 1999; Blau et al., 2009) explain a significant part of the gender wage gap in an accounting sense. As a result, policy makers are increasingly interested in policies promoting the participation of women in these high-earnings, male-dominated fields.[2] Whether these policies will contribute to reducing the gender wage gap is, however, an empirical question.

In this paper we study the returns to pursuing college majors in technology and engineering (TE) for men and women.[3] We link individual data on applications to higher education in Chile to administrative records on earnings and fertility, and exploit quasi-random assignment of applicants into specific major-college combinations. Our results reveal high returns for men to enrolling in a degree in TE as opposed to a degree in arts, humanities and social science (HASS). Enrollment into a TE field increases annual earnings by $\sim$ 74% ($ 7,345 USD) for men aged 30 to 36. Instead, we find no evidence of positive returns for women. We report that positive returns to TE fields for men are primarily driven by effects at the top of the earnings distribution. Enrolling in TE has a large, positive effect (18.8 p.p.) on the probability of men earning above $30,000 a year, but no effect on the same probability for women, which is consistent with the hypothesis of a *glass ceiling* preventing women from reaching the top of the earnings distribution (Bertrand, 2018). Gender differences in returns to TE fields are partly the consequence of a 29% increase in men's employment and a (statistically insignificant) 6% reduction in women's employment.

Our estimates for the returns to TE fields stand in contrast to observational earnings comparisons between students enrolled in TE and HASS, even after conditioning on measures of ability. Figure 2 shows how, conditional on math test scores, average earnings of both men and women at age 35 are almost twice as much for individuals who enrolled in TE as for those who enrolled in

[1] Source: NCES, 2016. Digest of Education Statistics. The percentage corresponds to persons holding a Bachelors degree in 2016, aged 25 to 34.

[2] The National Science (NSF) and the National Institutes of Health (NIH) have sponsored a number of initiatives aimed at increasing undergraduate students' interest in studying science, technology, engineering and math (STEM), improving STEM bachelor's degree completion rates generally, and improving STEM completion rates among women.

[3] We prefer to focus on TE rather than on STEM fields, mainly because many majors in science (particularly life sciences) are fairly balanced in terms of gender, and many majors in math are not particularly high-earning majors.

any other HASS field. This contrast suggests that women enrolling in TE fields are a self-selected group which should not be directly compared to those enrolling in other fields.

We overcome this selection problem by exploiting discontinuities in college admission generated by Chile's centralized application system to higher education. Like in most other countries – but unlike in the U.S. – prospective students in Chile apply to specific majors within college institutions (we refer to the combination of a major and a college as a *program*). Applicants are allowed to rank up to 10 programs in order of preference and the assignment problem is solved by a deferred-acceptance algorithm (Gale and Shapley, 1962). Each applicant is offered admission to their highest ranked program for which their composite test score is above a program-specific admission cutoff. Under the assumption that potential outcomes change smoothly across admission cutoffs, we can reasonably attribute discontinuities in observed outcomes to differences in admission.

Our paper's main contribution is to be the first to investigate gender differences in the returns to choosing one field compared to another. Although other papers have shown that career dynamics may differ for men and women in specific fields (see for instance Bertrand et al., 2010,) this does not necessarily imply that such fields are not profitable for women since similar dynamics may also exist in alternative fields. Using data from Chile, Hastings et al. (2013) find no gender differences in the returns to different fields compared to an outside option. Our analysis differs from theirs in that we use information on fallback alternatives as in Kirkeboen et al. (2016). For each application made to a program in TE, we have information on the program into which the applicant would be assigned in case of failing to qualify for admission in that program. This allows us to focus on applicants in the margin of being admitted into specific pairs of fields. Specifically, we focus on prospective students applying to programs in both TE and HASS fields, and whose composite test scores leave them near the margin of being admitted to either one or the other.[4]

Our finding of significant gender differences in the returns to TE fields does not extend to other high-earnings fields where females have higher rates of enrollment. We report that the returns for females to pursuing programs in business, a typically gender-balanced field, are high and very similar to those for men. We also find similar returns for men and women to pursuing programs in the female-dominated health field. This suggests that gender gaps in returns are a unique feature of male-dominated fields such as TE, and provides a plausible rationale for the low participation of women in these fields.

The absence of positive returns to TE for women appears to be a consequence of them failing to fully integrate into *the men's club*. Although men and women who initially enroll in TE are similarly likely to earn a degree in a TE field, their paths appear to diverge after college gradua-

[4] This includes both students who rank a TE degree program above a HASS degree program, and whose composite test score is near the admission cutoff for the TE degree program, and those who rank HASS above TE and are near the admission cutoff for the HASS alternative.

tion. In particular, we find that enrolling in TE, as opposed to HASS, increases the probability of employment at high-paying industries for men, but not for women. Similarly, enrollment into TE increases the probability of employment at male-dominated industries for men but not for women. Women's underrepresentation in high-paying and male-dominated industries could be partly the result of gender differences in preferences for job attributes. For instance, graduates from TE fields tend to work longer hours (see Appendix Figure A.1), which could be particularly burdensome for women because of the costs it imposes on childbearing (Goldin, 2014). Alternatively, it might be related to the costs associated with being a minority in a male-dominated environment, such as the lack of mentoring and networking, or a hostile *macho culture* (Kahn and Ginther, 2017).[5]

We finalize by studying the effects of pursuing TE fields for men and women on fertility and marriage market outcomes. We do not find effects of TE on fertility for either men or women. Enrollment in TE does not affect age at first birth or the total number of children for men and women of ages 19 to 36. Although we do not have data on marriage, for individuals with children we are able to identify the child's other parent. Overall, there do not seem to be relevant returns for either men or women in the marriage market (Goldin, 1992, 2006). Nevertheless, we do find a marginally significant 11 p.p. negative effect on the probability of women having a partner with yearly earnings above $15,000, which could be seen as a negative effect for women of enrolling in a TE field. Even though we only have proxy data on marriage, this is the first paper to look at the causal effect of accessing a given field of study on both, partners' ability and partners' earnings.

## 2 The Chilean Higher Education System

The Chilean postsecondary education sector consists of 60 universities that offer college degrees and 122 institutions that offer technical degrees. College degrees typically take 5 years to complete on time. Of the total number of universities, 33 participate in a centralized admission system called SUA (for *Sistema Único de Admisión*, or Unified System of Admission).[6] Universities that do not participate in this admission system are predominantly private and typically serve lower-scoring students. The 33 universities that participate in SUA are all not-for-profit, but can be public, private, or private-parochial. These universities span a wide range of selectivity levels.

Students applying to these 33 institutions must take an SAT-like standardized test called PSU (for *Prueba de Selección Universitaria* or University Selection Test.) Students sign up online to take the PSU during their senior year of high school, and everyone must take the test on the same day by the end of the academic year in November. There is only one chance to take the test each year. All students take exams in mathematics and language, and they can choose whether to take optional tests in science and history. Scores for these tests are scaled to a distribution with range

[5]See Cortes and Pan, 2017 for a review of the literature on gender and choice of occupation.

[6]Before 2012, only 25 Universities participated in the centralized admission system.

150 to 850 and a mean and median of 500. Entrance exam scores, along with high-school GPA, and GPA ranking[7] are the primary components of the composite scores used for postsecondary admissions.

After taking the PSU and being informed of their test scores, students submit their applications to the system using an online platform. As in many other postsecondary education systems, students in Chile apply directly to specific majors within postsecondary institutions (we refer to the combination of a major and a college as a *program*). As a reference, students applying in 2017 could choose from a total number of 1,477 programs in institutions participating in the centralized admission system. Each year, institutions must define ex-ante the weights each program will give to the different sections of the PSU as well as to high school GPA and GPA ranking. For instance, the composite admission score to a medicine major at *Pontificia Universidad Católica de Chile* gives a high weight to the science section of the PSU and no weight to the history section. Let $s_i^\iota$ be the score obtained by student $i$ in PSU section $\iota$ (e.g., math, history, or GPA). The program-specific weighted score of student $i$ applying to program $j$ is computed as:

$$s_{ij} = \sum_{\forall \iota} s_i^\iota \cdot \alpha_j^\iota,$$

where $\alpha_j^\iota$ is the weight given to PSU section $\iota$ in program $j$, with $\sum_{\forall \iota} \alpha_j^\iota = 1$ for any program $j$. Note that, because $\alpha_j^\iota$ vary across programs, the same student may have different weighted scores for different programs. The weights are public information and thus applicants can know beforehand what their weighted scores would be for each available program.

In their applications, students submit a list with up to ten programs ranked from most to least preferred.[8] Students have an incentive to rank programs correctly, meaning that they should not list a less-preferred choice over a more-preferred choice. However, they may incorporate admission probabilities when deciding which options to list, as they are capped at ten options.

Once students submit their applications, the system takes their rankings of alternatives, their program-specific scores, and the number of available seats by program, and implements a *deferred acceptance* assignment algorithm (Gale and Shapley, 1962) to determine which students are offered admission to each program. The algorithm generates program-specific admission cutoffs such that (i) each student is offered admission to his highest-ranked program for which his program-specific weighted score is equal to or above the program-specific admission cutoff (if any), and (ii) the number of students assigned to each program is equal to or less than the number of available seats for that program. While students apply with some knowledge of where they might be admitted, cutoff scores vary unpredictably from year to year due primarily to shocks in de-

[7] The GPA ranking was introduced in 2012 as a variable for admission. It measures a student's GPA ranking variable relative to previous cohorts' average GPA

[8] Up until 2011 students could submit only 8 options, but as of 2012 they can submit up to ten choices

mand. Student's inability to precisely predict cutoff scores is consistent with the imprecise control condition required for unbiased regression discontinuity estimation (Lee and Lemieux, 2010).

The admission process has two rounds. During the first round, students receive at most one admission offer and decide whether to enroll, remain in the waitlist for a more-preferred program from which they were rejected, or withdraw from the application process. The seats that remain empty after the first round are then allocated in a second round of offers. These second offers are generated following the same mechanism as the first round. In March of the following year, enrolled students begin their studies in their program. If students want to change to a different program they usually need to wait a whole year and participate in the next admission process on equal terms with other applicants.

# 3 Data and Sample Construction

## 3.1 Data

This study uses a unique dataset that brings together education, earnings, and fertility administrative records. To do so, we digitized hard copies of published test score results stored in a local newspaper (*El Mercurio*) for all students taking the standardized admission test in the 1999 to 2008 period and merged this information with educational, earnings, and fertility administrative records.[9] We chose to focus on students who graduated from high school between 1999 and 2008 because these were the oldest cohorts for whom we could gather complete higher education application records. These students were between 26 and 36 years old in 2017 which is the last time we observe them.

Educational records for these students include: socioeconomic information that students provide when signing up for the standardized admission test, their performance on the standardized college admission test and high school GPA, the application they submitted to the centralized system of admission, and whether they enrolled in any university participating in the centralized system of admission in the 2000 to 2017 period.

Because enrollment records for the 2000 to 2017 period are only available for institutions participating in the centralized system if admission, we complement this information with more recent administrative records that capture enrollment and graduation for all higher institutions in the country. This allows us to analyze, for example, the probability that a student enrolls or graduates from a program in a given field within any institution. These records, however, are only available for the 2007 to 2017 period, which is why when looking at these outcomes we focus on students

[9]Data from *El Mercurio* allowed us to gather information on students' unique national identification numbers (NIDs) and test score results. With the support of the Ministry of Labor we were able to add data on earnings and fertility records using students' NIDs.

graduating from high school between 2006 and 2009.[10]

In our analysis we group programs using their OECD category, with a few adjustments. Table 1 describes the 9 categories that we analyze and examples of programs contained in each category. Because we are looking at relatively young cohorts we choose to leave out programs in Law and Medicine, as these programs take too long to complete and data on earnings may be misleading. We choose to build a separate category for business & administration that is typically categorized under social sciences because we believe it differs considerable from other programs in this field. We also choose to build a separate category for architecture, that is typically categorized under TE. Finally, we leave aside the services field as it contains very few and diverse programs, and add programs in journalism, which are under this category, to the social science field.[11]

Earnings records are obtained from the unemployment insurance records of Chile's Ministry of Labor, which keeps track of the monetary contributions to the individual unemployment insurance account of each worker. The unemployment insurance covers almost the entire formal sector. The groups excluded from the insurance are workers with training contracts, workers under the age of 18, those in domestic service, pensioners, self-employed or own-account workers, and public-sector employees. We complement this data with records from the public-sector for the 2017-2018 period. Our data will prevent us from seeing the self-employed which represent approximately 15% of individuals in our sample, and it will give us an incomplete picture of public-sectors employees which represent approximately 20% of individuals in our sample.[12] Also, the maximum earnings are capped at $5,000 a month. In our data, roughly 0.2% of individuals with positive earnings are at this cap at age 28 and 11% of individuals with positive earnings are at this cap at age 36. Importantly, accessing a program in TE does not affect the probability of being at this cap.

Lastly, fertility records were obtained from the civil registration system. For each individual in our dataset, we are able to obtain birth records for each of their offsprings. The data also provides us a unique id for each child that allows us to determine whether two individuals in our data have a child together. Using this information we are able to build education and earnings records for an individuals' partner (i.e. father or mother of her child). However, we are only able to get information on an individual's partner if he happens to be in our records, which is the case for roughly 65% of individuals who have a child.[13]

[10] Table A.1 in the Appendix describes in detail the cohorts that we use for each of our analysis.

[11] Other small adjustments include excluding programs in industrial design and food engineering from the TE category, as these are rather low-earnings female-dominated programs.

[12] Table A.2 in the Appendix uses data from the Chilean household survey for 2017 (Casen, 2017) to characterize the percentage of individuals aged 28 to 36 who graduated from each field and who are unemployed, working in the private sector, working in the public sector, or self-employed

[13] We are unable to identify those partners who never signed up for the standardized admission test or who signed up prior to 1999.

### 3.2 Sample Construction

Our sample is composed of all students with composite test scores that leave them on the margin of admission to either a TE field or a HASS field. This includes i) students ranking a program in a TE field above a program in a HASS field, and whose composite score is near the admission cutoff for the TE program, and ii) students ranking a program in a HASS field above a program in a TE field, and whose composite score is near the admission cutoff for the HASS program. We pool together both samples in order to improve statistical power. We define the admission cutoff for program $j$, denoted by $c_j$, as the minimum weighted score among students who were offered admission to that program $j$ in the first round, that is:[14]

$$c_j = \min_i \{s_{ij}\} \quad s.t.\ i \text{ is offered admission to } j$$

We also define the running variable $r_{ij}$ as follows:

$$r_{ij} = \begin{cases} s_{ij} - c_j & \text{if } j \in TE \\ c_j - s_{ij} & \text{if } j \in HASS \end{cases}$$

Under this definition, a student will be offered admission to a program in TE if $r_{ij} \geq 0$, and to a program in HASS if $r_{ij} < 0$.

As several papers have pointed out, however, this admission cutoffs may not be relevant for some of the alternatives included in a student's application (e.g., Abdulkadiroğlu et al., 2014). Take for instance the case of a student $i$ who ranks first program $k$ with very low selectivity, followed by program $j$ with very high selectivity. For this student, crossing $j$'s admission cutoff would have no effect on assignment to $j$, because the less selective but preferred program $k$ is within reach when $r_{ij} = 0$. In this case, including $i$'s application to $j$ in our dataset would reduce the strength of our first stage, thus lowering statistical power and increasing the risk of weak instruments bias.

We deal with this issue following in spirit Dustan (2018), and eliminating from our sample any application to a program $k$ by a student $i$ if there exists a program $j$ such that both:

i) $i$ ranks $j$ above $k$, and

ii) $j$ is *relatively less selective* than $k$ from $i$'s perspective,

were relative selectivity is defined as follows:

***Definition 1*** *(Relative Selectivity)* *Let* $\phi_{ij} = \frac{r_{ij}}{\sqrt{\sum_{\forall \iota} (\alpha_j^{\iota})^2}}$ *be the euclidean distance between i's vector*

[14] An alternative would be to define cutoffs as the weighted score of the last student to enroll in $j$.

*of scores, $(s_i^\iota)_{\forall\iota}$, and the admission line for j defined as $C_j = \{(s^\iota)_{\forall\iota} : \sum_{\forall\iota} s^\iota \alpha_j = c_j\}$. Then program j is said to be relatively more selective from i's perspective than program $k \neq j$ if and only if $\phi_{ij} < \phi_{ik}$.*

It is easy to check that for the special case where programs $j$ and $k$ assign the same weights to each section of the test, relative selectivity of $j$ and $k$ depends exclusively on the comparison between $c_j$ and $c_k$. Approximately 55% of the applications survive the elimination process described by i) and ii).

Finally, we will exclude from our sample applications to programs that are not oversubscribed. In practice, we consider a program $j$ to be oversubscribed if at least one student among $j$'s applicants ends up being assigned to an alternative that is less preferred.

### 3.3 Sample Description

Table 2 presents summary statistics for the individuals in our sample and shows how they compare to the general population of high school graduates who signed up for the standardized admission test in 1999-2005.

Of the students who sign up for the PSU, 52% are females, and 43% live in the capital. Their households are composed of 4.6 individuals, where approximately 1.3 work. Sixty eight percent of households are headed by the father. Little over one quarter of these students has mothers with a tertiary education, and one third has fathers with a tertiary education. Two thirds of them have a father that works full time, but only a third has a mother that works full time. Students have an average GPA of 5.6, and score around 500 points on the math and language PSU. Twelve years after high school graduation, students report average annual earnings of \$7,408, and 6 months worked. Fertility records indicate that 65% of them have children by 2017.

The sample of students used in the analysis has a higher socioeconomic status and is more academically advantaged. This seems reasonable considering that they are close to the admission cutoff for at least one oversubscribed program in the centralized system of admission. These students have more educated parents. They also have higher GPAs and perform much better in the language and math PSU test. In terms of income, they report average annual earnings of \$6,875 twelve years after high school graduation. They are also less likely to have children (only 54% of them have children). Conditional on having children they tend to have them later.

## 4 Empirical Strategy

The admission process generates unpredictable admission cutoffs into different programs which, for a subset of applicants, effectively randomizes admission offers to either TE or a HASS fields. Our empirical strategy rests on the idea that applicants whose test scores leave them sufficiently near a margin involving both TE and HASS should be comparable in terms of observable and unobservable characteristics regardless of their actual admission. This allows us to estimate causal effects of admission into TE as opposed to HASS by comparing the outcomes of applicants who were marginally admitted to a program in TE and whose counterfactual admission would have been a program in HASS, to the outcomes of applicants who were marginally admitted into HASS and whose counterfactual admission would have been a program in TE.

Our reduced-form results are based on the following standard regression discontinuity specification:

$$y_{ijts} = \pi_{1s} \cdot r_{ijt} + \pi_{2s} \cdot (Z_{ijt} \times r_{ijt}) + \tau \cdot Z_{ijt} + \mu_{jt} + \eta_s + \varepsilon_{ijts} \qquad , s = 12..18, \tag{1}$$

where $y_{ijts}$ is the outcome of interest for student $i$ in margin $j$ (i.e., a given pair of programs, one of them in TE and the other in HASS), applying for admission in year $t$, observed $s$ years after high school graduation. The running variable $r_{ijt}$ determines whether $i$ is assigned into TE (i.e., $r_{ijt} \geq 0$) or HASS (i.e., $r_{ijt} < 0$), and $Z_{ijt}$ is a cutoff-crossing indicator (i.e., $Z_{ijt} = 1 \iff r_{ijt} \geq 0$). Following a standard practice in multi-cutoff RD studies, we include fixed effects at the level of variation of admission cutoffs (i.e., application year $\times$ program). To gain precision, we also include fixed effects for the students' counterfactual program, as well as the number of years elapsed since high school graduation. The slope parameters $\pi_{1s}$ and $\pi_{2s}$ are allowed to vary over time. Our parameter of interest is $\tau$, which recovers the effect of a marginal admission offer into a TE field on the outcome, averaged between 12 and 18 years since high school graduation. In some figures, we will also allow $\tau$ to vary with $s$ in order to describe how the effects evolve over time.

Most of our outcomes vary with $s$, including earnings, employment, employment sector, whether the individual has a child, and number of children. In these cases, we use a panel and estimate Equation 1. However, other outcomes, such as whether a students graduated from a program, or the characteristics of the peers he encountered when he enrolled for the first time, remain constant throughout time. In these cases our data will be cross-sectional, and Equation 1 will not vary across $s$.

In most cases, and in order to gain efficiency, we will estimate the model jointly for men and women, allowing $\tau$ as well as the slope parameters to vary by gender. The model is estimated by weighted ordinary least squares, using a triangular kernel around $r_{ijt} = 0$, with bandwidth $h = 35$, and clustering standard errors at the individual level.

Our IV results, on the other hand, are based on the following structural equation:

$$y_{ijts} = \delta_{1s} \cdot r_{ijt} + \delta_{2s} \cdot (Z_{ijt} \times r_{ijt}) + \beta \cdot d_{ijt} + \xi_{jt} + \zeta_s + \epsilon_{ijts} \qquad , s = 12..18, \tag{2}$$

where $d_{ijt}$ is a binary indicator taking the value 1 if the individual ever enrolls in the TE program of margin $j$. This model is estimated by weighted two stages least squares, using $Z_{ijt}$ as the instrument for $d_{ijt}$, and a triangular kernel with bandwidth $h = 35$. The effect of ever enrolling in a program in TE will be captured by our estimate of $\beta$. As in the reduced form case, we will typically estimate the model jointly for men and women, allowing $\beta$ as well as the slope parameters to vary by gender. The exclusion restriction for this structural specification requires an admission offer made to a program in TE to affect outcomes only through affecting the probability of enrollment in that program.

# 5 Empirical Results

## 5.1 RD Validation

We begin by presenting standard tests of the validity of our RD strategy. First, we perform balancing checks to examine whether individuals just above and just below the cutoff are similar in terms of their baseline observable characteristics. We focus on a set of socioeconomic variables, including family size, parents' education, and parents' work status. Large and significant discontinuities in the conditional means of these variables at the cutoff could be taken as an indication that potential earnings of individuals may also be discontinuous at the cutoff, thus violating the exclusion restriction.

Table 3 presents balance checks for male and female students in our sample. The table reports differences in means between students who were marginally assigned to TE and those who where marginally assigned to HASS. These differences are separately estimated for men and women from a specification analogous to (1), where the baseline characteristic is used as the dependent variable. Coefficients are all small in magnitude and precisely estimated indicating that students at either side of the cutoff are very similar to each other. Also, an F-test for each sample rejects that estimates are jointly significant.

Manipulation of PSU scores is highly implausible, not only because of the institutional setting, but also because students do not know ex-ante what the cutoff score will be for a given program. Still, to check for any signs of manipulation, we test for a discontinuity in the density of the standardized weighted score around the cutoff. Figure 3 shows histograms of scores for males and females in our sample. In both cases we find no visible sign of a discontinuity in the density around the cutoff.

### 5.2 First Stage

We continue by showing evidence of the relevance of admission cutoffs for individuals' assignment and enrollment. We say that an individual *ever enrolled* in $j$ if he enrolled in $j$ sometime between his application year and 2017.

Figure 4 pools together all the applications that meet the restrictions outlined in section 3.2 and illustrates how crossing the cutoff affects males and females': (i) probability of ever enrolling in the TE cutoff program, (ii) probability of ever enrolling in any program in a TE field, and (ii) probability of ever enrolling in any program in a HASS field.

The effects of assignment to the cutoff TE program on males and females' enrollment are illustrated in Figures 4. The figure shows that the probability of ever enrolling in the cutoff TE program jumps to about 55% at the cutoff for both males and females. Note that this probability is slightly above zero to the left side of the cutoff. This is the consequence of applicants retaking the standardized test in subsequent years and reapplying to the cutoff program. Also, the probability falls monotonically for scores to the right of the cutoff as higher-scoring students are assigned to more-preferred programs. Figures 4 also shows the effect of crossing the cutoff on applicants' probability of ever enrolling in any program in a TE or HASS fields. Crossing the admission cutoff increases the probability that the applicant will ever enroll in a program in a TE field by 40 p.p., and it decreases the probability that he or she will ever enroll in a program in a HASS field by 35 p.p.

To see what it means for an applicant to attend a program in a TE field, we study the effects of enrollment in TE on the characteristics of the peers that students encounter when they enroll for the first time. Table 4 reports two-stages least squares estimates, where a cutoff-crossing indicator is used as an instrument for ever enrolling in the cutoff program, and the characteristics of peers in students' program are used as the dependent variable. The table shows that male students assigned to a HASS field attend attend programs where 50% of students are males. This percentage increases by 26 p.p. for students enrolling in the TE cutoff program, meaning that 76% of their peers are men. In the case of women, the fraction of male peers increases by 21 p.p. from 44% in the case of women assigned to a HASS field to 65% for those enrolling in the TE cutoff program. Enrolling in a TE field also means that students encounter peers with higher math test scores (altough this effect is statistically significant for women only) and lower language test scores (statistically significant for men only).

### 5.3 Effects of accessing a TE field on earnings and employment

We now turn to our main results. We begin by studying the effect of accessing a program in a TE field as opposed to a program in a HASS field on individuals' earnings. Figure 5 offers a visual display of our results. The Figures shows, separately for men and women, non-parametric representations of earnings averaged through ages 30 to 36, conditional on the value of the running variable. We find evidence of a large and positive discontinuity at the cutoff for males and no evidence of a discontinuity for females, meaning that an admission offer to a program in TE increases annual earnings for men, but not so for women.

These results are confirmed by the estimates presented in Table 5. The table shows the effects for men and women of enrolling in a program in a TE field, as opposed to a HASS field on annual earnings between ages 30 to 36. The reported coefficients correspond to 2SLS estimates of $\beta$ in equation (2). Column 1 reports estimates on total earnings, while columns 2 to 6 report estimates on earnings distribution.

Our estimates of the returns to enrollment in a TE field are positive and statistically significant at the 1% for men, indicating a $7,345 increase in earnings. This effect correspond to an increases of 74% in baseline earnings. Instead, estimates are negative and statistically insignificant for women. Interestingly we find that most of the positive effects on men's earnings corresponds to a large increase in the probability of earning above $30,000 a year. In contrast, women are not more likely to earn more than $30,000 a year if enrolling in a TE field. While the probability of earning more than $30,000 a year is about 9% for both men and women enrolling in HASS fields, the same probabilities are 28% and 8% for men and women who end up enrolling in TE fields. These findings are consistent with the idea of there being a "glass ceiling" for women [see Bertrand, 2017 for a recent review on the phenomenon].

Figure 5 shows model estimates for the evolution of mean earnings over the life cycle, for men and women who i) where marginally assigned to and enrolled in a HASS field (blue lines), and ii) where marginally assigned to and enrolled in a TE field (red lines.) The plots show that earnings for both men and women tend to grow steadily with age in both TE and HASS fields. They also show that the effects of enrollment in TE, corresponding to the difference between the red and the blue lines, are stable over time.

Enrolling in a TE field also appears to affect the extensive margin. Table 6 shows effects on employment for men and women. Column (1) shows that even though women who enrolled in HASS fields tend to be employed more months than men who enrolled in HASS fields, enrollment into a TE field appears to increase male employment by 1.5 months a year (29%), while reducing female employment by 0.35 months a year (-6%), although this last result is nonsignificant. Consistent with this, we find positive (negative) effects for men (women) on the probability of men working at least one month in a year, as well as on the probability of them working every month of the year (columns (2) and (3)). Columns (4) and (5) show that the positive effect on male employment is concentrated on jobs with permanent contracts. Even though men in HASS fields are less likely to have a permanent contract than women in HASS fields (41% vs. 48%,) men in TE fields are considerably more likely to have a permanent contract (56% vs. 48%.) Although these effects are marginally significant, they accumulate over time resulting in 14.2 additional months of experience for men by the time they are 30-36 years old, and no change in experience for women of the same age (column (6)).

### 5.4 Robustness Checks

Part of the gender differences in returns to TE fields may be due to the fact that men and women apply to different programs in TE and HASS fields. For instance, among applicants who rank first a program in TE, women might be more likely to rank second a program in sociology, while men might be more likely to rank second a a program in acting. If earnings in sociology are higher than in acting, we might expect to see lower average returns for women than for men. Although this would not affect the validity of our estimates, it might affect their interpretation.

To see if this is driving our results, we re-estimate the earnings model using the same 2SLS specification, but re-weighting the data in such a way that the distribution of women's applications looks the same as the distribution of men's applications. Specifically, we weight women's observations by $\phi^m_{jt}/\phi^f_{jt}$, where $\phi^g_{ijt}$ is the fraction of gender $g$ applicants in margin $j$ at year $t$. We focus only on margins where there is a common support for men and women, that is, $0 < \phi^m_{ijt}, \phi^f_{ijt} < 1$. The results of this analysis, shown in Appendix Table A.3, are very similar to the unweighted analysis, suggesting that our results are not driven by gender differences in application patterns.

Our results may also be due to differences in ability of male and female applicants. Two applicants in the same margin of admission and with the same composite test score, might still differ in terms of their test scores at individual sections of the test, or in terms of their GPAs. For instance, women in the margin of admission to a TE program might have higher language test scores and lower math test scores than men in the same margin of admission. In fact, female students in our sample have slightly higher GPAs, and slightly lower math and language test scores. To test for this possibility, we run a model allowing for heterogeneous effects on GPA, math test score, and language test score. The results are shown in Appendix Table A.4. Although our estimates show some evidence of effect heterogeneity by academic performance, allowing for additional heterogeneity does not significantly affect our estimates of mean effects for men and women.

### 5.5 Contrast with other fields

In this section, we show that the gender differences observed in the returns to TE fields are not observed in the case of high-earnings fields that are more gender-balanced or female-dominated, such as business and administration or health.[15]

[15] In the analysis we leave aside program in business and accounting that are typically classified as business and administration, but that tend to have low-earnings. We also leave aside degrees in kinesiology, nutrition, obstetrics and occupational therapy that are typically classified as health, but that tend to have low-earnings.

Table 7 shows estimates of the effects of enrollment into programs in business and administration(columns 1-3) and health (columns 4-6). We observe large positive effects of enrolling in business and administration for both men and women. Although returns are slightly higher for men the difference is nonsignificant. We also observe positive, although nonsignificant, effects of enrolling in health for both men and women. These results suggest that there is something intrinsically different in TE that makes it unprofitable for women despite being profitable for men.

### 5.6 Explaining gender differences in returns to TE

#### *5.6.1 Differences in graduation patterns*

Heterogeneous returns for males and females could be a result of differences in graduation outcomes. Both males and females have a hard time persisting in STEM fields. Only a fraction of students who enroll in college expecting to major in a TE field actually finish one.[16] This is not just due to students dropping out, but also to students switching from STEM to non-STEM fields. While true for both genders, dropping out of STEM has been shown to be particularly common among women. Prior studies suggest that this is not due to differences in preparation (Arcidiacono et al., 2012; Astorne-Figari and Speer, 2019, 2018; Kugler et al., 2017; Ost, 2010; Price, 2010)[17], but could rather be a consequence of differences in competitiveness (Astorne-Figari and Speer, 2019; Buser et al., 2014; Fischer, 2017), gender composition of faculty and students (Carrell et al., 2010; Griffith, 2010; Hoffmann and Oreopoulos, 2009; Kugler et al., 2017; Rask and Bailey, 2002), future labor market considerations (Bronson, 2014; Gemici and Wiswall, 2014; Zafar, 2013), or gender differences in preferences for grades (Kugler et al., 2017; Rask and Bailey, 2002; Rask and Tiefenthaler, 2008).

In this section we analyze the extent to which our results could be driven by differences in graduation outcomes. We look at the effects of accessing a program in TE on (i) the probability of earning any university degree, (ii) the probability of graduating from any program in a TE field, (iii) the probability of graduating from the cutoff TE program, (iv) the probability of graduating from any university program on-time, where we define on-time graduation as having graduated within 6 years of high school graduation, (v) number of years enrolled in a university program, and (vi) number of year enrolled in a TE program. Because graduation outcomes are only available as of 2007, our analysis considers cohorts who graduated from high school between 2004 and 2007, and who presumably should not have graduated from a university degree prior to 2007.

The results of this analysis are shown in Table 8. Enrollment in a TE program increases stu-

[16] See Arcidiacono et al. (2016); Astorne-Figari and Speer (2019, 2018); Fischer (2017); Griffith (2010); Kugler et al. (2017); Ost (2010); Price (2010); Rask (2010); Stinebrickner and Stinebrickner (2013)

[17] An exception is Griffith (2010) who finds that differences in preparation can explain a large portion of the gender difference in STEM attrition

dents' probability of graduating from any university degree, although results are non-significant. However, it has a strong effect on the probability of graduating from a TE program. While only 4% of men who initially enrolled in a HASS program end up graduating from a TE program, 42% of those who enroll in the cutoff TE program obtain a degree in TE. Estimates are slightly smaller, but still strong for women. If two percent of women initially enrolling in HASS end up graduating from a TE program, this fraction increases to 32% for those who enrolled in TE. Importantly, gender differences in the effects of enrollment in TE on the probability of graduating from TE are not statistically significant. We thus conclude that gender differences in returns to TE are not driven by differences in graduation patterns but are rather the result of men and women's careers diverging after college graduation.

#### 5.6.2 *Industry of employment*

In this section, we investigate the role of differential effects on industry of employment by gender. Table 9 shows the effects of enrollment in a TE field on the probabilities of men and women being employed in an industry in the primary, secondary, finance and service sectors. Although significance is below conventional levels for most coefficients, it seems like enrollment in TE drives men and women out of the service sector and into the primary and secondary sectors. The positive effect on secondary sector employment for men is large (12 p.p.) and statistically significant, while the same effect for women is only 4 p.p. and statistically insignificant. There also seems to be a positive effect on the probability of being employed in the finance sector, but only for men.

To see what these patterns mean in terms of earnings potential, we estimate the effects of enrolling in TE on average earnings at the industry of employment. We define earnings potential of an individual $i$ of gender $g$ at time period $t$ as $Y^{p}_{itg} = \sum_l \bar{Y}_{ltg} \cdot I_{itl}$, where $\bar{Y}_{ltg}$ is the average earning of gender $g$ workers in industry $l$ at time $t$, [18] and $I_{itl}$ is a binary indicator for whether individual $i$ is employed in industry $l$ at time $t$. The effects of enrollment in TE on potential earnings are shown in column 6 of table 9. We find that enrolling in TE results in men working in higher-paying industries. Specifically, potential earnings increase by \$2,392, representing a 38% increase relative to baseline potential earnings. In contrast, we find small, negative and statistically insignificant effects on potential earnings of women.

Furthermore, in column 7 of Table 9 we show that enrollment into TE has a large and significant effect on the probability of men working on a male-dominated industry (i.e., an industry with at least 70% of male workers.) This probability increases from 16% to 33% for men who, induced by a marginal admission offer, enroll in TE rather than in HASS. In contrast, we find small and statistically insignificant effects on the probability of women working in male-dominated indus-

[18] We compute this average using all workers in our data, except those in our estimation sample. We let $l = 0$ denote the outside option (i.e., not working) and use $\bar{Y}_{0tg} = 0$

tries.

Overall, these findings suggest that the absence of positive returns to TE for women is at least in part the result of them employing themselves in different jobs as men. The literature has identified many factors behind gender differences in occupation. On the supply-side, these factors include differences in preferences for workplace flexibility, attitudes towards risk and competition, preferences for social contribution versus money and success, personality traits and skills, and costs associated with being a minority in a male-dominated environment, such as the lack of mentoring and networking, or a hostile *macho culture*. (see Cortes and Pan, 2017 for a review of this literature.) Demand-side explanations, on the other hand, include gender discrimination in employment.

#### *5.6.3 Fertility and child penalty*

Differential returns for men and women could be related to childbearing. Children pose a significant cost on the careers of women, something that has been documented by numerous studies (Waldfogel, 1998; Lundberg and Rose, 2000; Sigle-Rushton and Waldfogel, 2007b,a; Correll et al., 2007; Paull, 2008; Bertrand et al., 2010; Wilde et al., 2010; Daniel et al., 2013; Fitzenberger et al., 2013; Goldin, 2014; Adda et al., 2017; Angelov et al., 2016; Goldin and Katz, 2016; Kleven et al., 2018, 2019). More importantly, these costs can vary across different occupations. As first highlighted by Goldin (2014), women with children might find it particularly hard to advance their careers in fields that disproportionally reward individuals who work long hours or work particular hours, as is typically the case in TE (see Appendix Figure A.1).

In this section we study the differential returns to enrolling in a TE field for women with and without children. This allows us to get a sense of the extent to which heterogeneous returns by gender could be explained by the difficulty that women have to make a career in TE compatible with childbearing. This analysis, however, cannot be strictly interpreted as causal, as enrolling in TE might have direct effects on fertility. We therefore begin by studying the effect of enrolling in a program in a TE field on: (i) the probability of having children, and (ii) the total number of children.

Figure 7 shows model estimates of (i) and (ii) at ages 19 through 36 for men (7a) and women (7b) who enroll in a HASS field (blue line) and in a TE field (red line). From this plot we conclude that fertility trends of men and women in TE fields are statistically indistinguishable from those of men and women in HASS fields. Regardless of gender and field of enrollment, the probability of having a child goes up from nearly zero at age 19 to 45-65% at age 36.

We next look at the returns of accessing a program in a TE field for individuals with and without children when they are 30 to 36 years old. Although the decision to have children is endogenous, the fact that we don't observe major differences in the probability of having children for individuals enrolling in TE and HASS makes us more confident about our analysis. These results are shown in Table 12. Although our estimates are noisy, the point estimates are positive for women without children, but negative for women with children, consistent with there being a larger child penalty for women in TE fields.

#### *5.6.4 Returns on the marriage market*

Pursuing a program in a TE field could have effects on marriage outcomes. On the one hand, it changes the characteristics of peers at an age where many partnerships are formed (see Table 4). On the other hand, it may make an individual more attractive as a partner, either because it is taken as a sign of quality or because of higher expected earnings. This could in turn have an effect on earnings, particularly for women, as their earnings are likely to be more affected by their spouse's wage.

Although we do not have data on marriage rates, unique ids for children allow us to identify whether two individuals in our sample have a child together. We use this information to characterize an individual's partner. Although noisy, our estimates give us a general sense of how accessing a program in TE can affect marriage outcomes for men and women. The results of Table 11 show estimates of the effect of enrollment in TE on the probability of having: an identified partner (column 1,)[19], a partner with high language and math test scores (columns 2 and 3,) a partner with a university degree (column 5,) a partner with a degree from a TE major (column 6,), and a partner who earns more than $15,000 a year (column 7.)

The large and significant positive effect on the probability of men having an identified partner is directly related to the positive effect of enrollment in TE on men's fertility. For most of the outcomes related to the partner, we reject the hypothesis of a null effect. The only exception is a marginally significant but large negative effect on the probability of women having a partner who earns more than $15,000 a year.

## 6 Conclusion

Exploiting an institutional setting that generates quasi-random assignment of applicants into different college programs, we have shown that enrollment in high-earnings, male-dominated fields such as TE increases employment and earnings for men but not for women. Different graduation patterns do not seem to explain these differences. Instead, the absence of returns to TE for women appears to be the result of men and women following different career paths. In particular, women enrolling in TE are less likely than men to end up working in high-paying and male-dominated industries.

[19] This is in practice the probability of having a child with an identified father.

Our findings offer a plausible rationale for the low participation of women in TE and caution against policies that incentivize women's participation in TE while disregarding their subsequent academic and labor market trajectories. At the same time, our results raise questions about how to best counteract the difficulties encountered by women trying to advance their careers in male-dominated environments.

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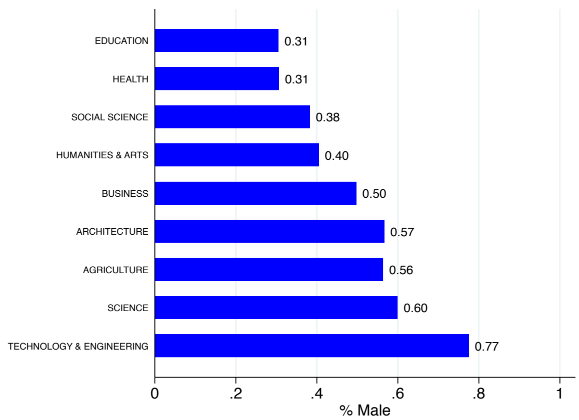
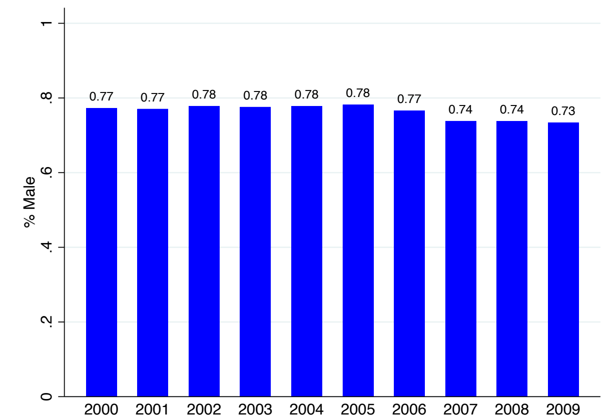
# Figures and Tables

**Figure 1:** Gender Composition of Fields



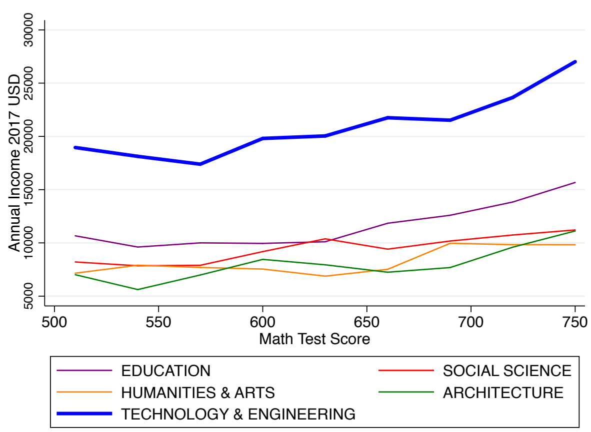

**(a)** Percentage of male enrollees by field



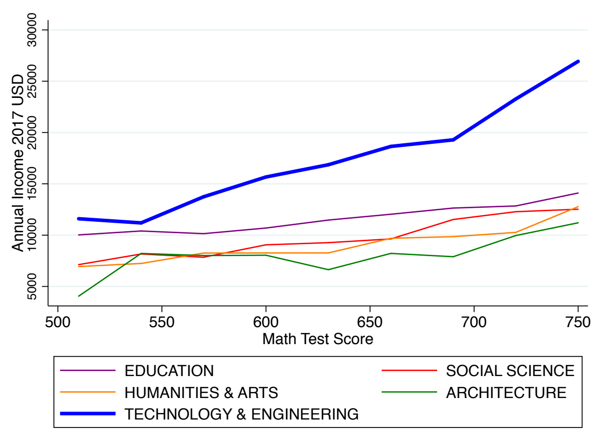

**(b)** Percentage of male enrollees in TE by enrollment year

Notes: Plot (a) shows the fraction of first-year enrollees who are male by field of study, averaged through cohorts enrolling between 2000 and 2006 – the same cohorts we consider in our earnings analysis. Plot (b) shows the fraction of first-year enrollees in TE who are male by year of enrollment.

**Figure 2:** Earnings for 35 years old men and women by field of study & academic performance



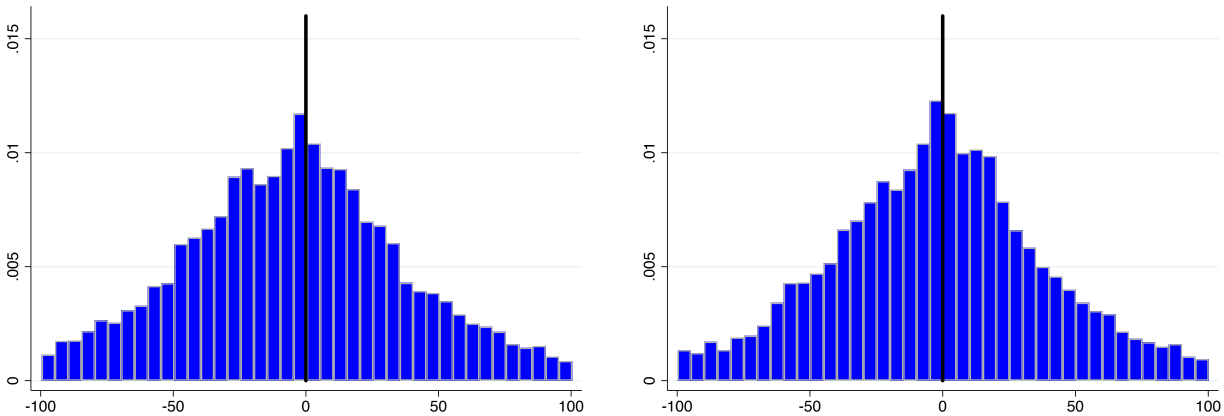

**(a)** Males




**(b)** Females

Notes: The figure shows, separately for students who enrolled in different fields, average earnings of males (a) and females (b) at age 35, at different levels of math test scores.

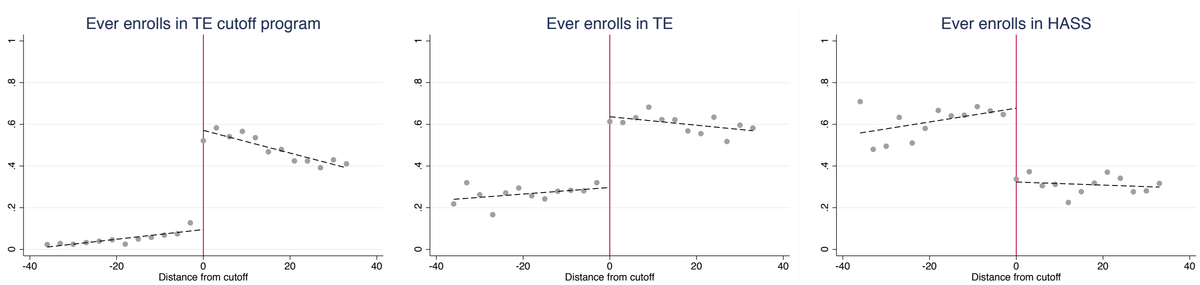
**Figure 3:** Histograms of the running variable



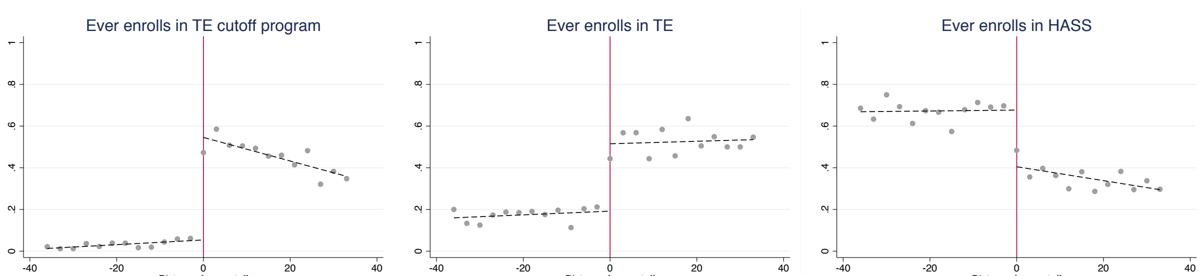

**(a)** Males **(b)** Females

Notes: The figure shows histograms of the running variable as defined in section **??**, separately for men (a) and women (b).

**Figure 4:** First Stage



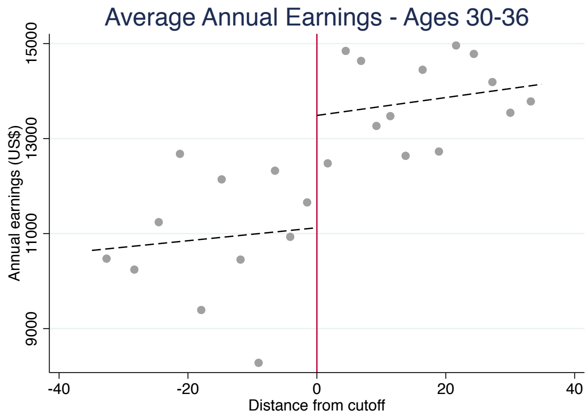

**(a)** Males



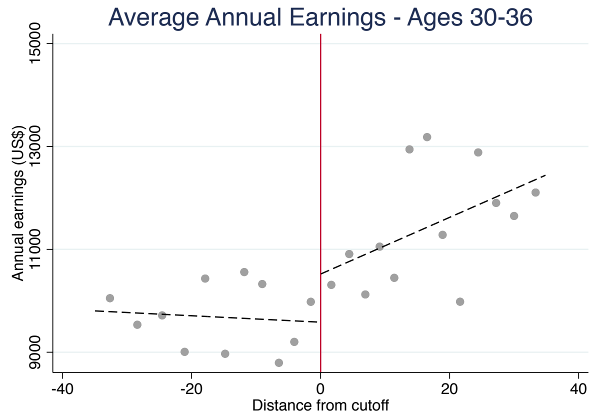

**(b)** Females

Notes: This figure shows for men (a) and women (b) how crossing the cutoff increases the probability of (i) ever enrolling in the TE cutoff program, (ii) ever enrolling in any program in TE, and (iii) ever enrolling in any program in HASS. In the case of (ii) and (iii), we focus exclusively on students who graduated from high school between 2006 and 2009, because only for these years we have enrollment records for the whole postsecondary system, including institutions not participating in the centralized admission system.

**Figure 5:** Effects on annual earnings



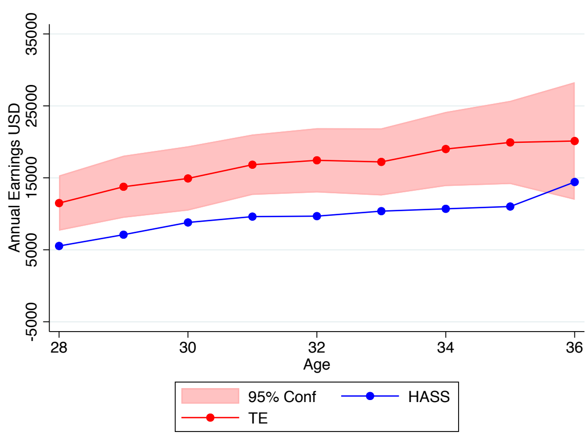

**(a)** Males



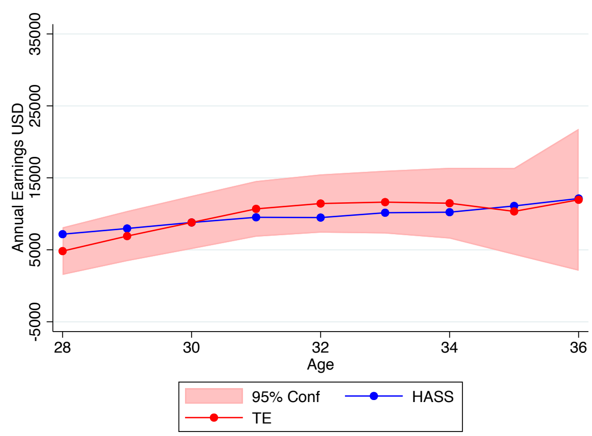

**(b)** Females

Notes: The figure shows for males (a) and females (b) graphical representations of mean earnings averaged through ages 30 to 36, conditional on the value of the running variable. Each gray dot represents the mean running variable (on the horizontal axis) and average annual earnings (on the vertical axis) of equally sized groups of applicants. Dashed lines show linear fits with slopes and intercepts allowed to differ at both sides of the cutoff.

**Figure 6:** Effects on annual earnings over time



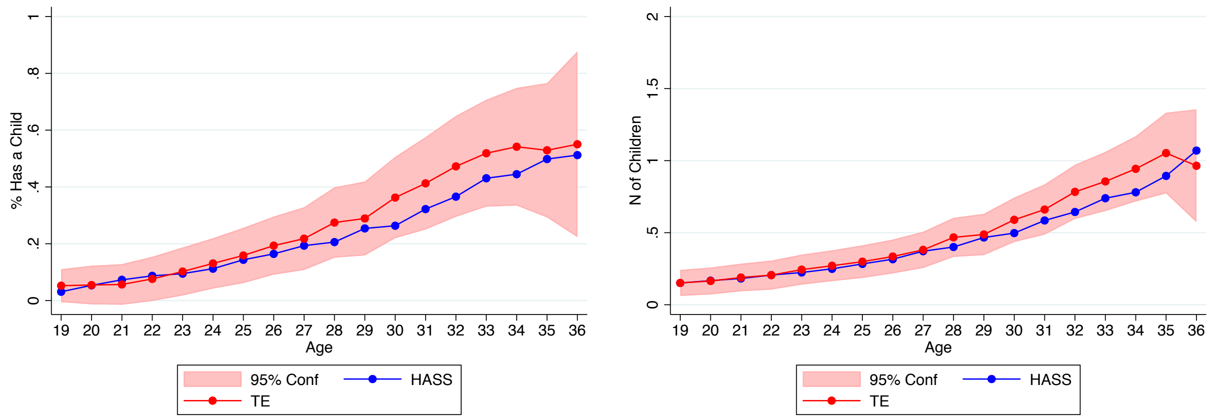

**(a)** Males



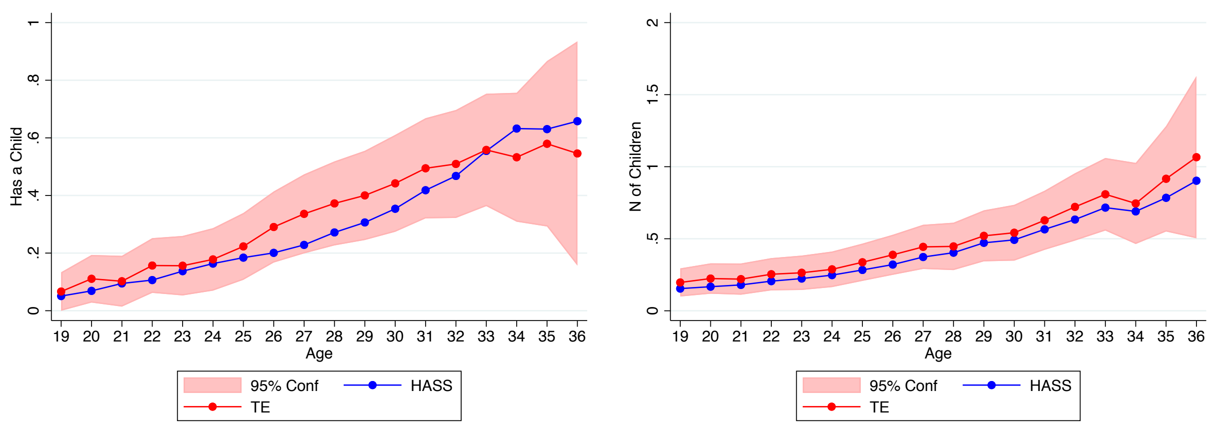

**(b)** Females

Notes: This figure shows for males (a) and females (b) model estimates of mean earnings at ages 28 to 36 for applicants who were in the margin of receiving an admission offer into either TE or HASS and who i) enrolled in TE induced by a marginal admission offer to TE (red line), or ii) enrolled in HASS induced by a marginal admission offer to HASS (blue line.) The difference between the red and the blue line represents the estimated causal effect of enrolling in TE as opposed to HASS. Although these effects are allowed to vary over time, the figure shows that they are stable for both men and women.

**Figure 7:** Effects on fertility over time




**(a)** Males




**(b)** Females

Notes: This figure shows for males (a) and females (b) model estimates of the probability of having a child (on the left), and the mean number of children (on the right), at ages 19 to 36 for applicants who were in the margin of receiving an admission offer into either TE or HASS and who i) enrolled in TE induced by a marginal admission offer to TE (red line), or ii) enrolled in HASS induced by a marginal admission offer to HASS (blue line.) The difference between red and blue lines represent estimated causal effects of enrolling in TE as opposed to HASS on fertility.

**Table 1:** Example programs in each field of study

| Category | Field of study | Example programs |
|---|---|---|
| **Technology & Engineering** | Engineering & Industry & Technology | Engineering, Construction, Computing |
| **Humanities & Arts & Social Science** | Education | Pedagogy |
| | Humanities & Arts | History, Design, Art, Translation and Interpretation, Language, Philosophy, Cinematography, Acting, Music |
| | Social Science | Psychology, Journalism, Sociology, Geography Anthropology, Political Science |
| | Architecture | Architecture |
| **Others** | Health | Nursing, Social Work, Nutrition, Chemistry and Pharmacy, Obstetrics, Kinesiology, Dentistry, Medical Technology, Phonoaudiology, Occupational Therapy |
| | Business & Administration | Business & Administration, Accounting, Audit, Public Administration |
| | Agronomy | Veterinary, Agronomy, Forest Engineering |
| | Science | Biology, Biochemistry, Physics, Astronomy, Geology, Math, Statistics, Chemistry |

Notes: This table shows example programs in each field of study. Our central results estimate the effects of enrollment in programs in the first category (TE) when the counterfactual is a program in the second category (HASS).

**Table 2:** Descriptive Statistics

| | Sample | | All | |
|---|---|---|---|---|
| | Mean | Std. Dev | Mean | Std. Dev |
| | (1) | | (2) | |
| Socioeconomic Characteristics | | | | |
| Female | 0.443 | 0.497 | 0.524 | 0.499 |
| Lives in the capital | 0.325 | 0.469 | 0.432 | 0.495 |
| Total HH members | 4.562 | 1.539 | 4.583 | 1.708 |
| Total HH members work | 1.292 | 0.684 | 1.325 | 0.765 |
| Head of HH father | 0.721 | 0.449 | 0.684 | 0.465 |
| Head of HH mother | 0.214 | 0.410 | 0.224 | 0.417 |
| Mother primary ed | 0.142 | 0.349 | 0.229 | 0.420 |
| Mother secondary ed | 0.500 | 0.500 | 0.493 | 0.500 |
| Mother tertiary ed | 0.359 | 0.480 | 0.278 | 0.448 |
| Father primary ed | 0.130 | 0.337 | 0.212 | 0.409 |
| Father secondary ed | 0.421 | 0.494 | 0.448 | 0.497 |
| Father tertiary ed | 0.448 | 0.497 | 0.340 | 0.474 |
| Father works full-time | 0.705 | 0.456 | 0.697 | 0.459 |
| Father works part-time | 0.121 | 0.326 | 0.121 | 0.326 |
| Mother works full-time | 0.358 | 0.479 | 0.342 | 0.474 |
| Mother works part-time | 0.055 | 0.227 | 0.058 | 0.234 |
| Academic Performance | | | | |
| GPA | 5.877 | 0.410 | 5.639 | 0.502 |
| Language Score | 571 | 78 | 489 | 117 |
| Math Score | 594 | 90 | 486 | 123 |
| earnings & Employment | | | | |
| Months Employed (12 years after HS) | 5.467 | 5.358 | 6.068 | 5.435 |
| Earnings (12 years after HS) | 6,875 | 9,443 | 7,408 | 9,825 |
| Fertility | | | | |
| Has Children | 0.543 | 0.498 | 0.648 | 0.478 |
| N of Children | 0.830 | 0.943 | 1.041 | 1.034 |
| Age at First Birth | 28.067 | 4.956 | 26.235 | 5.040 |
| Obs | 4,420 | | 986,118 | |

Notes: This table shows descriptive statistics for applicants in our analysis sample (column 1) and for everyone who signed up for taking the admission test between 1999 and 2007 (column 2). Socioeconomic characteristics are obtained from a survey taken at test registration; academic performance data are obtained from official records from the Ministry of Education; earnings and employment data are obtained from administrative sources (unemployment insurance for private sector earnings, government payrolls for public sector earnings. )

**Table 3:** Balance

| | Male | | Female | |
|---|---|---|---|---|
| | Mean Control | T-C | MeanControl | T-C |
| Socioeconomic Characteristics | | | | |
| Lives in the capital | 0.306 | 0.005 | 0.324 | $-0.016$ |
| | | ( 0.026) | | ( 0.033) |
| Total HH members | 4.706 | $-0.102$ | 4.538 | 0.060 |
| | | ( 0.159) | | ( 0.168) |
| Total HH members work | 1.277 | 0.077 | 1.175 | 0.092 |
| | | ( 0.075) | | ( 0.077) |
| Head of HH father | 0.756 | $-0.020$ | 0.699 | 0.032 |
| | | ( 0.046) | | ( 0.055) |
| Head of HH mother | 0.178 | 0.033 | 0.219 | $-0.054$ |
| | | ( 0.044) | | ( 0.049) |
| Mother primary ed | 0.217 | $-0.084^{**}$ | 0.107 | 0.010 |
| | | ( 0.040) | | ( 0.038) |
| Mother secondary ed | 0.428 | 0.060 | 0.493 | 0.033 |
| | | ( 0.053) | | ( 0.062) |
| Mother tertiary ed | 0.356 | 0.024 | 0.401 | $-0.043$ |
| | | ( 0.052) | | ( 0.060) |
| Father primary ed | 0.143 | 0.023 | 0.138 | $-0.074^{*}$ |
| | | ( 0.041) | | ( 0.038) |
| Father secondary ed | 0.401 | 0.018 | 0.433 | $-0.041$ |
| | | ( 0.055) | | ( 0.064) |
| Father tertiary ed | 0.456 | $-0.041$ | 0.429 | $0.115^{*}$ |
| | | ( 0.055) | | ( 0.064) |
| Father works full-time | 0.693 | 0.010 | 0.564 | $0.189^{***}$ |
| | | ( 0.050) | | ( 0.061) |
| Father works part-time | 0.124 | 0.011 | 0.146 | $-0.017$ |
| | | ( 0.036) | | ( 0.040) |
| Mother works full-time | 0.279 | $0.107^{**}$ | 0.365 | $-0.063$ |
| | | ( 0.050) | | ( 0.059) |
| Mother works part-time | 0.059 | $-0.008$ | 0.029 | 0.021 |
| | | ( 0.026 ) | | ( 0.030) |
| F-test | | 0.772 | | 1.548 |
| | | $p < 0.380$ | | $p < 0.214$ |
| N Clusters | 2,152 | | 1,628 | |

Notes: This table shows that most pre-enrollment covariates change smoothly across the cutoff for both male and female applicants. Although we do see significant differences for some covariates between observations at the left and right side of the cutoff, a joint F-test does not reject the hypothesis of all covariates being balanced.

**Table 4:** Effect of accessing a TE program on peer characteristics

| | Peers: | | | |
|---|---|---|---|---|
| | %Male | Avg. GPA | Avg. Lang. Test Score | Avg. Math Test Score |
| | (1) | (2) | (3) | (4) |
| Ever Enrolls | | | | |
| Men | 0.26*** | −0.11** | −29.28*** | 11.16 |
| | ( 0.05) | ( 0.05) | ( 8.79) | ( 8.72) |
| Women | 0.21*** | −0.03 | −13.12 | 20.38** |
| | ( 0.04) | ( 0.05) | ( 8.92) | ( 9.00) |
| Men-Women | 0.04 | −0.08 | −16.16 | −9.22 |
| | ( 0.06) | ( 0.06) | ( 11.65) | ( 11.53) |
| Baseline Mean | | | | |
| Men | 0.50 | 5.94 | 576.03 | 584.41 |
| Women | 0.44 | 5.95 | 579.13 | 581.11 |
| N Clusters | 2,222 | 2,222 | 2,222 | 2,222 |

Notes: This table shows 2SLS estimates for men and women of the effects of enrollment into a TE program on the characteristics of peers in the program students actually enroll. Cutoff-crossing indicators interacted with gender are used as instruments. Baseline estimates correspond to mean earnings of men and women who, induced by a marginal admission offer, enrolled in a HASS field. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

**Table 5:** Effect of Enrolling in a TE program on Earnings

| | Total Earnings (1) | $I = 0$ (2) | $0 < I \leq 10k$ (3) | $10k < I \leq 20k$ (4) | $20k < I \leq 30k$ (5) | $I > 30k$ (6) |
|---|---|---|---|---|---|---|
| Ever Enrolls | | | | | | |
| Men | $7,345^{***}$ | $-0.125^{*}$ | $-0.022$ | $-0.017$ | $-0.007$ | $0.188^{***}$ |
| | ( 2,314) | ( 0.067) | ( 0.026) | ( 0.029) | ( 0.022) | ( 0.050) |
| Women | 265 | 0.038 | $-0.020$ | $-0.011$ | $0.051^{**}$ | $-0.007$ |
| | ( 2,156) | ( 0.079) | ( 0.034) | ( 0.035) | ( 0.025) | ( 0.041) |
| Men-Women | $7,079^{**}$ | $-0.163$ | $-0.002$ | $-0.006$ | $-0.058^{*}$ | $0.195^{***}$ |
| | ( 3,077) | ( 0.101) | ( 0.042) | ( 0.043) | ( 0.032) | ( 0.064) |
| Baseline Mean | | | | | | |
| Men | 9,872 | 0.448 | 0.094 | 0.072 | 0.058 | 0.090 |
| Women | 9,939 | 0.408 | 0.093 | 0.101 | 0.031 | 0.087 |
| N Clusters | 4,308 | 4,308 | 4,308 | 4,308 | 4,308 | 4,308 |

Notes: This table shows 2SLS estimates for men and women of the effects (averaged between ages 30 to 36) of enrollment into a TE program on annual earnings (column 1) as well as on the probability of earnings falling in several ranges (columns 2-6). Cutoff-crossing indicators interacted with gender are used as instruments. Baseline estimates correspond to mean outcomes for men and women who, induced by a marginal admission offer, enrolled in a HASS field. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

**Table 6:** Effect of Enrolling in a TE program on Employment

| | N of months employed in a year (1) | Works at least one month (2) | Worked every month (3) | Permanent Contract (4) | Fixed-term Contract (5) | N of months of experience (6) |
|---|---|---|---|---|---|---|
| Ever Enrolls | | | | | | |
| Men | $1.52^{**}$ | $0.12^{*}$ | $0.13^{**}$ | $0.15^{**}$ | $-0.06$ | $14.20^{**}$ |
| | ( 0.77) | ( 0.07) | ( 0.06) | ( 0.06) | ( 0.05) | ( 5.97) |
| Women | $-0.35$ | $-0.04$ | $-0.02$ | 0.00 | $-0.08$ | 0.79 |
| | ( 0.91) | ( 0.08) | ( 0.07) | ( 0.08) | ( 0.05) | ( 6.71) |
| Men-Women | 1.87 | 0.16 | 0.14 | 0.15 | 0.02 | 13.40 |
| | ( 1.15) | ( 0.10) | ( 0.09) | ( 0.10) | ( 0.07) | ( 8.73) |
| Baseline Mean | | | | | | |
| Men | 5.31 | 0.55 | 0.31 | 0.41 | 0.26 | 40.36 |
| Women | 5.95 | 0.59 | 0.37 | 0.48 | 0.21 | 45.04 |
| N Clusters | 4,308 | 4,308 | 4,308 | 4,308 | 4,308 | 4,308 |

Notes: This table shows 2SLS estimates for men and women of the effects (averaged between ages 30 to 36) of enrollment into a TE program on several employment outcomes. Cutoff-crossing indicators interacted with gender are used as instruments. Baseline estimates correspond to mean outcomes for men and women who, induced by a marginal admission offer, enrolled in a HASS field. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

**Table 7:** Effects of Enrolling in Health or Business

| | Business vs. HASS | | | Health vs. HASS | | |
|---|---|---|---|---|---|---|
| | Annual earnings (1) | N of months employed in a year (2) | Works at least one month (3) | Annual earnings (4) | N of months employed in a year (5) | Works at least one month (6) |
| Ever Enrolls | | | | | | |
| Men | $8,246^{**}$ | 0.15 | 0.13 | $4,182$ | $-0.08$ | $-0.03$ |
| | ( 3,655) | ( 0.10) | ( 0.10) | ( 7,245) | ( 0.20) | ( 0.20) |
| Women | $4,988^{**}$ | 0.05 | 0.06 | $4,185$ | 0.08 | 0.08 |
| | ( 2,530) | ( 0.07) | ( 0.07) | ( 3,365) | ( 0.11) | ( 0.10) |
| Men-Women | $3,258$ | 0.10 | 0.07 | $-3$ | $-0.16$ | $-0.11$ |
| | ( 4,525) | ( 0.12) | ( 0.12) | ( 7,785) | ( 0.22) | ( 0.22) |
| Baseline Mean | | | | | | |
| Men | 13,395 | 0.65 | 0.42 | 10,985 | 0.61 | 0.42 |
| Women | 13,094 | 0.64 | 0.45 | 10,897 | 0.50 | 0.36 |
| N Clusters | 5,326 | 5,326 | 5,326 | 2,453 | 2,453 | 2,453 |

Notes: This table shows 2SLS estimates for men and women of the effects (averaged between ages 30 to 36) of enrollment into i) a program in a Business field (columns 1-3) or ii) a program in a Health field (columns 4-6), on earnings and employment. Cutoff-crossing indicators interacted with gender are used as instruments. Baseline estimates correspond to mean outcomes for men and women who, induced by a marginal admission offer, enrolled in a HASS field. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

**Table 8:** Effect of accessing a degree in a TE program on graduation

| | Graduates: | | | | | |
|---|---|---|---|---|---|---|
| | Any Univ. program (1) | Any program in TE (2) | Cutoff program (3) | Any Univ. program On-time (4) | Years Enrolled (5) | Years Enrolled in TE (6) |
| Ever Enrolls | | | | | | |
| Men | 0.16 | $0.38^{***}$ | $0.40^{***}$ | 0.02 | $-0.34$ | $3.36^{***}$ |
| | ( 0.10) | ( 0.07) | ( 0.05) | ( 0.09) | ( 0.56) | ( 0.46) |
| Women | 0.09 | $0.30^{***}$ | $0.35^{***}$ | $-0.14$ | 0.56 | $3.21^{***}$ |
| | ( 0.11) | ( 0.08) | ( 0.06) | ( 0.11) | ( 0.58) | ( 0.54) |
| Men-Women | 0.07 | 0.08 | 0.05 | 0.15 | $-0.91$ | 0.15 |
| | ( 0.15) | ( 0.10) | ( 0.08) | ( 0.13) | ( 0.79) | ( 0.69) |
| Baseline Mean | | | | | | |
| Men | 0.38 | 0.04 | -0.03 | 0.20 | 5.54 | 0.71 |
| Women | 0.38 | 0.02 | -0.03 | 0.22 | 5.58 | 0.44 |
| N Clusters | 3,850 | 3,850 | 3,850 | 3,850 | 3,850 | 3,850 |

Notes: This table shows 2SLS estimates for men and women of the effects (averaged between ages 30 to 36) of enrollment into a TE program on several graduation outcomes. Cutoff-crossing indicators interacted with gender are used as instruments. Baseline estimates correspond to mean outcomes for men and women who, induced by a marginal admission offer, enrolled in a HASS field. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

**Table 9:** Effect of enrolling in a TE program on Employment Sector

| | Employment Sector | | | | | Avg. Earnings in sector | Male dominated sector (>70% male) |
|---|---|---|---|---|---|---|---|
| | Works at least one month | Primary sector | Secondary sector | Finance | Services | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Ever Enrolls | | | | | | | |
| Men | $0.12^{*}$ | 0.02 | $0.12^{**}$ | 0.05 | $-0.06$ | $2,392^{**}$ | $0.17^{***}$ |
| | ( 0.07) | ( 0.03) | ( 0.06) | ( 0.05) | ( 0.04) | ( 1,037) | ( 0.06) |
| Women | $-0.04$ | 0.02 | 0.04 | $-0.00$ | $-0.08$ | $-316$ | 0.03 |
| | ( 0.08) | ( 0.02) | ( 0.07) | ( 0.06) | ( 0.06) | ( 1,130) | ( 0.05) |
| Men-Women | 0.16 | 0.01 | 0.08 | 0.05 | 0.02 | $2,708^{*}$ | $0.14^{*}$ |
| | ( 0.10) | ( 0.04) | ( 0.09) | ( 0.07) | ( 0.07) | ( 1,501) | ( 0.07) |
| Baseline Mean | | | | | | | |
| Men | 0.56 | 0.02 | 0.23 | 0.14 | 0.14 | 6,220 | 0.16 |
| Women | 0.58 | 0.00 | 0.17 | 0.14 | 0.22 | 6,924 | 0.07 |
| N Clusters | 4,308 | 4,308 | 4,308 | 4,308 | 4,308 | 4,239 | 4,308 |

Notes: This table shows 2SLS estimates for men and women of the effects (averaged between ages 30 to 36) of enrollment into a TE program on the probability of working at least one month (column 1), the probability of working in different sectors (columns 2-5), the average earnings of workers in the industry of employment (column 6) and the probability of employment in a male-dominated industry (column 7). Cutoff-crossing indicators interacted with gender are used as instruments. Baseline estimates correspond to mean outcomes for men and women who, induced by a marginal admission offer, enrolled in a HASS field. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

**Table 10:** Effect of enrolling in a TE program for women with and without children

| | Earnings<br>(1) | N of months employed in a year<br>(2) | Works at least one month<br>(3) | Worked every month<br>(4) | Permanent Contract<br>(5) | Fixed-term Contract<br>(6) |
|---|---|---|---|---|---|---|
| Men | | | | | | |
| Ever Enrolls | | | | | | |
| No Children | $5,341.96^{*}$ | 1.43 | 0.12 | 0.09 | $0.16^{**}$ | $-0.05$ |
| | ( 2,731.37) | ( 0.97) | ( 0.08) | ( 0.08) | ( 0.08) | ( 0.06) |
| Children | $9,388.53^{**}$ | 1.36 | 0.10 | 0.16 | 0.12 | $-0.09$ |
| | ( 3,779.29) | ( 1.16) | ( 0.10) | ( 0.10) | ( 0.10) | ( 0.08) |
| Difference | $-4,046.57$ | 0.07 | 0.02 | $-0.06$ | 0.04 | 0.04 |
| | ( 4,595.30) | ( 1.48) | ( 0.13) | ( 0.13) | ( 0.13) | ( 0.10) |
| Baseline Mean | | | | | | |
| No Children | 9,050.99 | 4.82 | 0.51 | 0.28 | 0.38 | 0.23 |
| Children | 11,317.31 | 6.13 | 0.63 | 0.35 | 0.46 | 0.30 |
| Women | | | | | | |
| Ever Enrolls | | | | | | |
| No Children | 3,089.43 | 0.31 | 0.02 | 0.03 | 0.08 | $-0.13^{*}$ |
| | ( 3,007.76) | ( 1.33) | ( 0.12) | ( 0.11) | ( 0.12) | ( 0.07) |
| Children | $-1,932.31$ | $-0.81$ | $-0.08$ | $-0.05$ | $-0.05$ | $-0.03$ |
| | ( 2,706.49) | ( 1.10) | ( 0.10) | ( 0.09) | ( 0.10) | ( 0.07) |
| Difference | 5,021.74 | 1.12 | 0.09 | 0.09 | 0.13 | $-0.09$ |
| | ( 3,785.12) | ( 1.64) | ( 0.15) | ( 0.13) | ( 0.14) | ( 0.10) |
| Baseline Mean | | | | | | |
| No Children | 8,434.17 | 5.39 | 0.54 | 0.32 | 0.43 | 0.22 |
| Children | 11,208.37 | 6.42 | 0.63 | 0.42 | 0.51 | 0.19 |
| N Clusters | 4,308 | 4,308 | 4,308 | 4,308 | 4,308 | 4,308 |

Notes: This table shows 2SLS estimates of the effects (averaged between ages 30 to 36) of enrollment into a TE program on earnings and employment for men and women with and without children. We use as instruments cutoff-crossing indicators interacted with gender and dummy variables for having children. Baseline estimates correspond to mean outcomes for men and women who, induced by a marginal admission offer, enrolled in a HASS field. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

**Table 11:** Effect of enrolling in a TE program on partner characteristics

| | Has a Partner<br>(1) | Has a Partner w/ High Lang. Score<br>(2) | Has a Partner w/ High Math Score<br>(3) | Has a Partner w/ Univ.<br>(4) | Has a Partner w/ TE Major<br>(5) | Has a Partner w/ Earn>15000<br>(6) |
|---|---|---|---|---|---|---|
| Ever Enrolls | | | | | | |
| Men | 0.06 | $-0.04$ | $-0.00$ | 0.02 | $-0.04$ | $-0.01$ |
| | ( 0.08) | ( 0.07) | ( 0.07) | ( 0.07) | ( 0.02) | ( 0.05) |
| Women | $-0.02$ | $-0.07$ | $-0.04$ | $-0.10$ | $-0.02$ | $-0.11^{*}$ |
| | ( 0.09) | ( 0.08) | ( 0.08) | ( 0.07) | ( 0.05) | ( 0.06) |
| Men-Women | 0.09 | 0.04 | 0.04 | 0.12 | $-0.02$ | 0.10 |
| | ( 0.12) | ( 0.10) | ( 0.10) | ( 0.09) | ( 0.05) | ( 0.08) |
| Baseline Mean | | | | | | |
| Men | 0.39 | 0.26 | 0.23 | 0.20 | 0.04 | 0.13 |
| Women | 0.38 | 0.26 | 0.25 | 0.21 | 0.08 | 0.20 |
| N Clusters | 4,308 | 4,308 | 4,308 | 4,308 | 4,308 | 4,308 |

Notes: This table shows 2SLS estimates for men and women of the effects (averaged between ages 30 to 36) of enrollment into a TE program on the probability of having an identified partner (column 1), having a partner with high language and math test scores (columns 2-3), having a partner with a university degree in any field (column 4) or in a TE field (column 5), and having a partner who earns more than $15,000. Cutoff-crossing indicators interacted with gender are used as instruments. Baseline estimates correspond to mean outcomes for men and women who, induced by a marginal admission offer, enrolled in a HASS field. Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

**Table 12:** Effect of enrolling in a TE program for women with more or less educated mothers

| | Earnings (1) | N of months employed in a year (2) | Works at least one month (3) | Worked every month (4) | Permanent Contract (5) | Fixed-term Contract (6) |
|---|---|---|---|---|---|---|
| Men | | | | | | |
| Ever Enrolls | | | | | | |
| Mother no Tertiary Ed. | $9,808^{***}$ | $2.26^{**}$ | $0.15^{*}$ | $0.20^{**}$ | $0.20^{**}$ | $-0.04$ |
| | ( 3,028) | ( 1.02) | ( 0.09) | ( 0.08) | ( 0.08) | ( 0.06) |
| Mother Tertiary Ed. | 3,374 | 0.58 | 0.12 | 0.01 | 0.07 | $-0.05$ |
| | ( 3,863) | ( 1.26) | ( 0.11) | ( 0.10) | ( 0.11) | ( 0.08) |
| Difference | 6,434 | 1.68 | 0.03 | 0.19 | 0.13 | 0.01 |
| | ( 4,899) | ( 1.62) | ( 0.14) | ( 0.13) | ( 0.14) | ( 0.10) |
| Baseline Mean | | | | | | |
| Mother no Tertiary Ed. | 7,748 | 5.00 | 0.54 | 0.27 | 0.38 | 0.26 |
| Mother Tertiary Ed. | 12,781 | 5.51 | 0.54 | 0.35 | 0.44 | 0.23 |
| Women | | | | | | |
| Ever Enrolls | | | | | | |
| Mother no Tertiary Ed. | $-2,456$ | $-1.07$ | $-0.08$ | $-0.09$ | $-0.05$ | $-0.09$ |
| | ( 2,557) | ( 1.12) | ( 0.10) | ( 0.09) | ( 0.10) | ( 0.06) |
| Mother Tertiary Ed. | $6,658^{*}$ | 1.58 | 0.07 | 0.17 | 0.15 | $-0.08$ |
| | ( 3,940) | ( 1.58) | ( 0.14) | ( 0.13) | ( 0.14) | ( 0.08) |
| Difference | $-9,113^{*}$ | $-2.65$ | $-0.15$ | $-0.27^{*}$ | $-0.20$ | $-0.01$ |
| | ( 4,666) | ( 1.91) | ( 0.17) | ( 0.16) | ( 0.17) | ( 0.10) |
| Baseline Mean | | | | | | |
| Mother no Tertiary Ed. | 10,178 | 6.31 | 0.62 | 0.42 | 0.51 | 0.21 |
| Mother Tertiary Ed. | 8,718 | 5.11 | 0.55 | 0.29 | 0.40 | 0.21 |
| N Clusters | 4,149 | 4,149 | 4,149 | 4,149 | 4,149 | 4,149 |

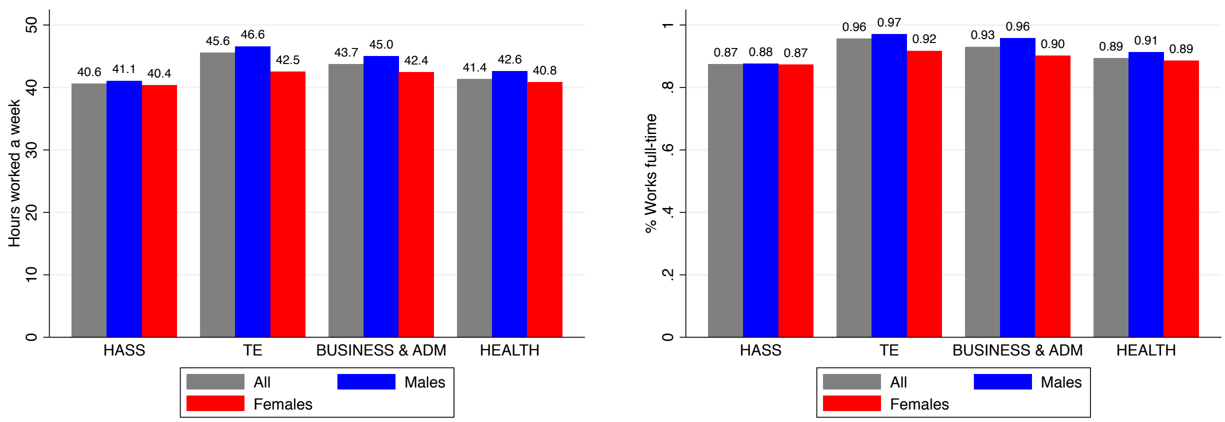
Notes: This table shows 2SLS estimates of the effects (averaged between ages 30 to 36) of enrollment into a TE program on earnings and employment outcomes for men and women with college-educated and non-college-educated mothers. We use as instruments cutoff-crossing indicators interacted with gender and dummy variables for mothers having tertiary education. Baseline estimates correspond to mean outcomes for men and women who, induced by a marginal admission offer, enrolled in a HASS field. Standard errors clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

# A Appendix - Additional Figures and Tables

**Table A.1:** Cohorts used in each of our analysis

| Cohort | Age last obs. | Descriptive | Balance | Peers | Earnings | Employment | Graduation | Children | Partner |
|---|---|---|---|---|---|---|---|---|---|
| 2000 | 36 | x | x | | x | x | | x | x |
| 2001 | 35 | x | x | | x | x | | x | x |
| 2002 | 34 | x | x | | x | x | | x | x |
| 2003 | 33 | x | x | | x | x | | x | x |
| 2004 | 32 | x | x | | x | x | x | x | x |
| 2005 | 31 | x | x | | x | x | x | x | x |
| 2006 | 30 | x | x | | x | x | x | x | x |
| 2007 | 29 | | | x | | | x | x | |
| 2008 | 28 | | | x | | | x | x | |
| 2009 | 27 | | | x | | | x | x | |
| 2010 | 26 | | | x | | | x | x | |

**Figure A.1:** Working hours by field of graduation




**(a)** Hours Worked a Week

**(b)** Percentage Employed Full-Time

Notes: This figure shows data from a nationally representative survey (CASEN 2017) on (a) the average number of hours worked a week and (b) the percentage of workers employed full-time, of male and female workers who graduated from different field categories.

**Table A.2:** Employment by field of graduation

| | | Employment | | | |
|---|---|---|---|---|---|
| | | Unemployed | Employed Private Sector | Employed Public Sector | Self Employed |
| | | (1) | (2) | (3) | (4) |
| **Field** | | | | | |
| TE | Male | 0.102 | 0.662 | 0.123 | 0.113 |
| | Female | 0.109 | 0.677 | 0.097 | 0.118 |
| HASS | Male | 0.088 | 0.484 | 0.245 | 0.182 |
| | Female | 0.133 | 0.470 | 0.294 | 0.102 |
| Business & Adm | Male | 0.139 | 0.511 | 0.158 | 0.192 |
| | Female | 0.176 | 0.613 | 0.100 | 0.111 |
| Health | Male | 0.183 | 0.252 | 0.413 | 0.153 |
| | Female | 0.123 | 0.306 | 0.503 | 0.068 |

Notes: This table shows data from a nationally representative survey (CASEN 2017) on the fraction of males and females graduating from each field category who where unemployed (column 1), employed in the private or public sectors (columns 2 & 3), or self-employed (column 4).

**Table A.3:** Effect of enrolling in a TE program on Earnings - Reweighted

| | Total Earnings | $I = 0$ | $0 < I \leq 10k$ | $10k < I \leq 20k$ | $20k < I \leq 30k$ | $I > 30k$ |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ever Enrolls | | | | | | |
| Men | $7,268^{***}$ | $-0.141^{**}$ | $-0.016$ | $-0.016$ | $-0.005$ | $0.183^{***}$ |
| | ( 2,429) | ( 0.069) | ( 0.027) | ( 0.029) | ( 0.022) | ( 0.053) |
| Women | $1,732$ | $-0.056$ | $0.036$ | $-0.008$ | $0.060^{*}$ | $0.026$ |
| | ( 3,172) | ( 0.100) | ( 0.042) | ( 0.039) | ( 0.034) | ( 0.063) |
| Men-Women | $5,536$ | $-0.085$ | $-0.052$ | $-0.008$ | $-0.065^{*}$ | $0.156^{**}$ |
| | ( 3,702) | ( 0.113) | ( 0.048) | ( 0.046) | ( 0.037) | ( 0.077) |
| Baseline Mean | | | | | | |
| Men | 9,835 | 0.461 | 0.088 | 0.076 | 0.051 | 0.096 |
| Women | 9,356 | 0.455 | 0.069 | 0.083 | 0.016 | 0.091 |
| N Clusters | 3,898 | 3,898 | 3,898 | 3,898 | 3,898 | 3,898 |

Notes: This table is analogous to Table **??**, but re-weights observations of women's applications in order to make their distribution of applications comparable to that of men (see section 5.4 for details). Standard errors clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1

**Table A.4:** Effect of enrolling in a TE program on Earnings - Heterogeneity by Ability

| | Annual earnings (1) | N of months employed in a year (2) | Works at least one month (3) | Works every month (4) |
|---|---|---|---|---|
| Ever Enrolls | | | | |
| Men | $6,036^{**}$ | 0.84 | 0.08 | 0.06 |
| | ( 2,845) | ( 1.02) | ( 0.09) | ( 0.08) |
| Women | 940 | $-0.15$ | $-0.02$ | 0.01 |
| | ( 2,260) | ( 0.94) | ( 0.08) | ( 0.08) |
| Men-Women | 5,096 | 0.99 | 0.10 | 0.05 |
| | ( 3,850) | ( 1.42) | ( 0.12) | ( 0.12) |
| Ever Enrolls × | | | | |
| GPA | $-1,152$ | $-0.05$ | $-0.04$ | $-0.01$ |
| | ( 3,955) | ( 1.58) | ( 0.14) | ( 0.13) |
| Math test score | $4,675^{**}$ | $1.96^{**}$ | $0.13^{*}$ | $0.18^{***}$ |
| | ( 2,244) | ( 0.84) | ( 0.07) | ( 0.07) |
| Language test score | $-3,423$ | $-1.06$ | $-0.07$ | $-0.10$ |
| | ( 2,755) | ( 0.96) | ( 0.08) | ( 0.08) |
| Baseline Mean | | | | |
| Men | 9,637 | 5.42 | 0.56 | 0.32 |
| Women | 9,514 | 5.81 | 0.58 | 0.36 |
| N Clusters | 4,308 | 4,308 | 4,308 | 4,308 |

Notes: This table studies heterogeneous effects on earnings and employment by measures of ability. The endogenous variable (i.e., a dummy variable indicating whether the applicant ever enrolled in the cutoff TE program) is included interacted with gender dummies as well as with GPA, and math and language test scores (all three adjusted to have a mean of zero at the cutoff.) Standard errors clustered at the individual level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$