Joining the Old Boys' Club: Women's Returns to Majoring in Technology and Engineering *

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Abstract.
We examine the economic consequences for women of majoring in the male-dominated fields of Technology and Engineering (TE). Using administrative records and admission discontinuities generated by Chile's centralized college admission system, we identify causal effects of field of study on labor market outcomes. Majoring in TE yields significant earnings gains for men, but not for women. These gendered returns are only partially explained by sorting across firms and sectors; the bulk reflects women being rewarded differently within similar environments. We also document that child-related earnings penalties are substantially larger for women in TE, suggesting parenthood-related barriers play an important role.
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1 Introduction

Women's role in economic life has changed dramatically over the last century. In the United States, the rate of female labor force participation more than doubled between 1920 and 2019.[1] Over the same period, women went from representing a small fraction of total college graduates to outnumbering men beginning in the 1980s (e.g., Goldin, 2021). As a result, women progressively entered fields and occupations once exclusively reserved for men. For instance, women were first admitted to Harvard Medicine School in 1945 and to Harvard Law School in 1950, but they quickly increased their numbers to become half of the medicine and law students in the United States today.

Despite this general trend, certain fields, particularly in STEM, remain heavily dominated by men (Kahn and Ginther, 2017). Specifically, we show that women are remarkably underrepresented in the fields of Technology and Engineering (TE). In the United States, 21.2% of Bachelor's degrees in TE granted in 2018-19 were conferred to women.[2] In Chile, the focus of our paper, women represent one-fourth of first-year students in these fields (see Figure 1). This stands in contrast with majors in the fields of science and math (SM), where women represent 52% of total enrollment in Chile and 56% of graduates in the U.S.[3] For this reason, our primary focus in this paper will be on TE rather than the broader STEM category.

Female under-representation in TE is perceived by many as problematic, partly because these fields miss out on women's contribution (Hsieh et al., 2019), and partly because women may be missing economic opportunities.[4] Accordingly, a growing number of public and private initiatives seek to encourage women's participation in these fields.

Do women benefit from pursuing college majors in TE? Descriptive evidence for the United States typically shows that college graduates with majors in TE earn higher wages than graduates from other majors, regardless of gender (e.g., Altonji et al., 2012, 2016). Our data for Chile

[1] It rose from 23.3% in 1920 (Killingsworth and Heckman, 1986) to 57.4% in 2019 (BLS, 2021). Both figures consider female population of ages 14 and over.

[2] Source: NCES (2020). Considers Bachelors' degrees conferred in computer and information sciences and support services (21% women) and engineering and engineering technologies (21% women).

[3] Source: NCES (2020). Considers Bachelors' degrees conferred in biological and biomedical sciences (63% women), mathematics and statistics (42% women), physical sciences and science technologies (41% women).

[4] 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.

reveals a similar picture. Figure 2 shows that, even after conditioning on math college admission test scores, both men and women who enrolled in TE earn higher wages than those who enrolled in other fields. These observational differences in earnings across fields may reflect causal effects, but they could also be a result of pre-existing differences in (potentially unobservable) characteristics of individuals choosing different fields. Importantly, since TE is such a rare choice among women, selection may be more of an issue in their case. This highlights the need for well-designed research identifying, separately for men and women, the causal effects of pursuing majors in TE.

In this paper we investigate the returns of majoring in TE for men and women. In line with Kirkeboen et al. (2016), we conceive the returns to a given field of study in opposition to other fields, focusing on students who switch between TE and non-TE programs. To obtain causal estimates, we exploit discontinuities originated in Chile's centralized college admission system. The system assigns applicants to *programs* (i.e., majors within college institutions) by implementing an algorithm that takes students' test scores and rankings of programs and generates program-specific admission cutoffs. Using information on test scores and rankings, we are able to identify applicants on the verge of being admitted to programs in different fields of study. Following Kirkeboen et al. (2016), we focus on these marginal applicants and use discontinuities as instruments for enrollment in different fields.

Our main results reveal contrasting stories for men and women. For men who have been out of high school between 11 and 20 years (i.e., predicted ages of 29 to 38), enrollment in TE increases yearly earnings by 8% ($1,954).[5] This effect is partly driven by a 4% increase in employment. However, we find no evidence of positive returns for women in the same cohorts. The positive returns for men of majoring in TE primarily stem from individuals transitioning from lower-earnings fields (such as education, humanities, arts, or social sciences). There are no positive effects from switching from health or business to TE, and only relatively small gains from switching from science to TE. For men, transitioning from lower-earning fields to TE results in a 26% ($4,133) annual increase in earnings. In contrast, women do not experience positive returns from enrolling in TE, regardless of their alternative field.

Importantly, we show that our finding of gendered returns in TE does not extend to other high-

[5] All figures are in 2019 USD.

earnings fields such as business or health, where women obtain similar or slightly higher returns than men. On the other hand, we report negative returns to enrolling in science for both men and women. This contrast suggests that there is something specific to TE that makes it profitable for men but not for women.

We explore several possible explanations for the gender differences in the returns to TE, taking advantage of our rich dataset with information on graduation, firm and sector of employment, marriage, and fertility. First, research has shown that women who pursue college majors in TE fields are graded more harshly and are more likely to switch majors or drop out than comparable men (e.g., Ahn et al., 2019; Astorne-Figari and Speer, 2019).[6] However, we show that our results are unlikely to be explained by gender differences in major persistence, as men and women who enroll in TE induced by a marginal admission offer are equally likely to graduate from these fields.

Second, women who graduate from TE majors may sort into less profitable firms than male TE graduates. Because of the gender composition of TE graduates, the firms demanding their skills tend to employ a larger fraction of men. Women may not seek jobs in these firms if they expect there to prevail exclusionary gender stereotypes and norms. Also, managers in these firms may be reluctant to hire women if they believe that doing so will lower male workers' morale, group cohesiveness or productivity (e.g., Goldin, 2014a; Akerlof and Kranton, 2000). In our analysis, we find that enrollment in TE shifts both men and women toward more TE-aligned and more male-dominated firms and sectors, but this reallocation is larger for men. Gender differences in the average earnings paid by employers account for approximately 30% of the overall earnings gap, reflecting both differential employment rates and the larger magnitude of men's sorting response. However, the bulk of the gap reflects differences in earnings within similar firms and sectors, which may be driven by barriers in wage bargaining, promotion, or access to professional networks that have been shown to shape women's career advancement relative to that of their male peers (e.g., Biasi and Sarsons, 2022; Cullen and Perez-Truglia, 2021; Casarico and Lattanzio, 2019; Sato and Ando, 2017). Consistent with this possibility, descriptive evidence from a survey we collected

[6] Available 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), 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).

among a selected sample of college graduates indicates that women who majored in TE—despite reporting stronger career orientation—are substantially more likely than men and than women in other fields to report experiencing discrimination in the workplace.

Third, majoring in TE may impact women's career progression by affecting their fertility or because family-friendly or flexible jobs may be particularly costly to obtain in TE (Goldin, 2014b; Goldin and Katz, 2016). In our analysis, we find that enrollment in TE does not affect women's fertility decisions, including the likelihood or timing of having children. However, we document that the earnings penalty associated with childbearing is larger for women in TE than in other fields consistent with male-dominated work environments being particularly unaccommodating of family responsibilities. This suggests that the within-firm barriers discussed above may partly operate through the interaction of gender and parenthood. In fact, a simple accounting exercise indicates that differences in child-related penalties could account for about one third of the gender gap in returns to TE.

Fourth, majoring in TE may impact women's career progression through affecting their marriage market outcomes. Although we observe individuals a bit early (i.e., when they are 30 to 38 years old), 50% of them show up as married in our dataset.[7] We find that women who enroll in TE are more likely to marry other TE enrollees and individuals with higher math and language scores, and we also find suggestive (but noisy) evidence that their partners have higher earnings on average. In standard household labor supply models, higher spousal earnings are expected to reduce women's own labor supply, providing a plausible channel through which marriage-market outcomes may affect observed earnings. At the same time, the magnitude of these marriage-market gains is economically meaningful—comparable to the positive labor-market returns to TE observed for men—suggesting that TE enrollment may generate substantial returns for women outside their own earnings, even if it does not raise their labor-market income.

Overall, our evidence points to a picture in which the gender gap in returns to TE is only partially explained by differences in where women work or whether they work at all. The remainder appears to reflect differences in how men and women are rewarded within similar work environ-

[7]We classify two individuals as married if they are legally married or if they had a child together. Unfortunately we can only get information on earnings, admission test scores and enrollment for 76% of partners in our sample (i.e., those who signed up to take the admission test in or after 1999.)

ments. While we cannot pinpoint the exact barriers that women face, our evidence points to the larger child penalty in TE as an important channel. Women may also benefit from TE enrollment through channels outside their own earnings, most notably through the marriage market, which could in turn shape their labor market decisions in ways that contribute to the gap.

Our paper contributes to the literature on heterogeneous returns to fields of study (see Altonji et al., 2016, for a detailed review.) This literature has established substantial differences in average earnings across fields of study and has documented persistent gender gaps in these returns. Most existing studies estimate returns by OLS, controlling for various covariates. While they often find a positive return to enrolling in TE,[8] these estimates may be biased due to selection on unobservables, particularly if individuals sort into fields based on comparative advantage or field-specific abilities. In this paper, we follow a more recent approach and exploit discontinuities in program assignments to provide causal estimates of the returns to enrolling in TE. Similar to Kirkeboen et al. (2016), we use information on individuals' rankings of alternatives and focus on applicants who are close to the margin between TE and non-TE fields. This feature of our data allows us to improve upon Hastings et al. (2013), who estimate returns to different fields in Chile but lack information on next-best alternatives and must therefore rely on strong assumptions about selection into fields. These assumptions may be particularly restrictive when studying gender differences, given that women who enroll in TE are likely to be more selected along unobserved dimensions than men.

Importantly, we analyze how returns to TE vary for men and women, a dimension that is not explored by Kirkeboen et al. (2016). While several studies in the returns-to-major literature report gender-specific estimates, these are typically based on observational comparisons and may reflect differences in selection into fields rather than causal differences in returns. In particular, selection on unobservables may differ by gender, given that women who enroll in male-dominated fields such as TE are likely to be more selected than men along dimensions that are difficult to observe. By exploiting quasi-experimental variation in program assignment, our design allows us to estimate gender-specific returns that do not rely on strong assumptions about selection into

[8] See Berger (1988); James et al. (1989); Hamermesh and Donald (2008); Webber (2014) cited in Altonji et al. (2016), who find a positive return to enrolling in TE compared to fields such as education. When examining gender differences, several papers find a higher premium for men than for women in TE Altonji (1993); Grogger and Eide (1995); Chevalier (2011); Del Rossi and Hersch (2008), though a few find the opposite result Rumberger and Thomas (1993); Loury and Garman (1995).

fields. We find that the positive returns to TE are driven by men, with no corresponding earnings gains for women. Our findings relate to recent evidence from Chile showing that access to selective, business-oriented programs increases the probability of reaching leadership positions and top earnings, but only for men from elite private high schools (Zimmerman, 2019). We extend this line of research by showing that even when women gain access to male-dominated TE fields, they do not experience positive earnings returns, highlighting the limits of field-of-study choices alone in reducing gender gaps in labor market outcomes.

We also contribute to the literature on the costs of childbearing (Kleven et al., 2019b) by showing that child penalties vary systematically across fields of study and are particularly large for women in TE. Together with our finding of limited effects of TE enrollment on fertility, this suggests that gender differences in returns to TE are shaped not by childbearing itself, but by how motherhood translates into earnings losses across fields. These patterns are consistent with the idea that occupations associated with TE offer fewer opportunities for flexible work arrangements (Goldin, 2014b; Goldin and Katz, 2016).

By examining marriage-market outcomes, we also contribute to the literature on the broader effects of higher education beyond own earnings (Kirkebøen et al., 2021). Previous studies show that attending more selective universities can affect marriage-market outcomes, including assortative matching on education and earnings (Kaufmann et al., 2013; Barrios Fernández et al., 2021). We build on this work by showing that field-of-study choices—rather than institutional selectivity—can also shape marriage-market matching. In particular, we find that women who enroll in TE are more likely to match with partners who have stronger academic profiles and higher earnings.

From a policy perspective, numerous initiatives aim to encourage women's enrollment in STEM. These policies seek to increase women's contributions in these fields and potentially increase their earnings. However, we show that the returns of enrolling in science are either null or negative depending on the alternative, and while the returns of enrolling in TE are positive for men, this is not the case for women. Therefore, at the margins we study, women do not experience any positive returns from enrolling in STEM, not even when compared to low-earning fields.

Our findings point to several mechanisms that may help explain gendered returns to TE, including gender-differentiated labor supply responses, differential sorting across firms within TE, and larger earnings penalties associated with parenthood in TE fields. More broadly, gender gaps in promotion and career progression within male-dominated firms may also contribute to these patterns. Taken together, our findings suggest that policies focused solely on increasing female enrollment in these fields may be insufficient, and should go hand in hand with policies that promote women's progression in male-dominated, high-paying work environments and improve the compatibility of these jobs with family responsibilities.

2 Institutional Setting

2.1 Gender gaps in Chile

Chile is a middle-income OECD member country, with a per capita GDP equal to about $25,000 after adjusting for purchasing power parity. This is among the highest in Latin America (World Bank, 2018). Although gender equality has advanced significantly in the past twenty years, there is still much progress to be made. Employment rates for women aged 25 to 54 rose from about 45% in 2000 to about 65% in 2018. Comparatively, employment rates for women in this age group are 73% in the United States, 65% in Colombia, 63% in Brazil, and 54% in Mexico. At the same time, the gender wage gap is 12.5%, compared to 18.2% in the United States, 5.8% in Colombia, and 14% in Mexico (OECD, 2018).

In terms of career advancements for women, the country lags behind more developed economies. Women are 50% less likely than men to hold managerial positions and occupy just 8% of board seats in large publicly listed companies. In contrast, the United States sees a 25% difference in managerial positions and 22% female board representation (OECD, 2018).

In line with many other Latin American countries, Chilean society tends to embrace more traditional gender roles compared to the U.S. According to data from the 2012 World Values Survey, 18% of Chileans believe men should have priority in scarce job situations and 34% think a woman earning more than her husband can cause problems. Moreover, 36% believe children suffer when mothers work, and 20% see university education as more crucial for boys. Additionally, 27% view men as better political leaders and 18% believe men make superior business executives (see Appendix Table A.1).

Our interpretation of these numbers is that Chile is halfway between other Latin American countries and higher-income countries like the United States in terms of the place of women in the economy, but closer to Latin America in terms of cultural views on gender.

2.2 College Admission in Chile

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. Of the total number of universities, 25 participate in a centralized admission system called SUA (for *Sistema Único de Admisión*, or Unified System of Admission).[9] Universities that do not participate in this admission system are predominantly private and typically serve lower-scoring students. The 25 universities that participate in SUA are all non-profit, but can be public, private, or private-parochial. These universities span a wide range of selectivity levels.

Students applying to these 25 institutions must take an SAT-like standardized test called PSU (for *Prueba de Selección Universitaria* or University Selection Test.) 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. Test scores and high school GPA are scaled to a distribution with a range of 150 to 850 and a mean and median of 500.

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*). Each year, institutions must define ex-ante the weights each program will assign to the different sections of the PSU as well as to high school GPA when ranking candidates.[10] Because weights can vary across programs, the same student may have different weighted scores for different programs.

In their applications, students submit a list of up to eight programs ranked from most to least preferred. 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

[9] Eight additional institutions joined the system in 2012, but our paper focuses on earlier admission processes.

[10] All programs allocate weight to students' GPAs, math scores, language scores, and an additional score which may be derived from their history or science scores, or whichever is the highest.

probabilities when deciding which options to list, as they are capped at eight 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. While students apply with some knowledge of where they might be admitted, cutoff scores vary unpredictably from year to year, primarily due to shocks in demand. Students' inability to precisely predict cutoff scores is consistent with the imprecise control condition required for unbiased regression discontinuity estimation (Lee and Lemieux, 2010).

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 an entire year and participate in the next admission process on equal terms with other applicants.

3 Data and Sample

3.1 Data

This study uses a dataset that brings together administrative records on education, earnings, fertility, and marriage. To do this, we digitized hard copies of published test score results stored in a local newspaper (*El Mercurio*) for all students taking the standardized admission test from 1999 to 2007 and merged this information with educational, earnings, marriage and fertility data (see Appendix B for more details on data construction). We chose to focus on students who graduated from high school between 1999 and 2007 because these were the oldest cohorts for whom we could gather complete higher education application records. These students were between 30 and 38 years old in 2019, which is the last time we observe them. For each individual we retain their first observed application.

Educational records for these students include: socioeconomic information that students provide when signing up to take admission tests, admission test scores, high school GPA, applications as submitted to the centralized admission system, and enrollment into any university participating in the centralized admission system between 2000 and 2017.

Because enrollment records for the 2000 to 2017 period are only available for institutions participating in the centralized system of admission, we complement this information with more recent administrative records that capture enrollment and graduation for all higher education 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 from any institution. These records, however, are only available starting in 2007, which is why when looking at these outcomes we focus on students graduating from high school in 2003 or later.

In our analysis, we classify programs using their Cine-UNESCO field categories. Figure 1a shows the percentage of enrollees between 2000 and 2008 in each field who were women. We focus our analysis on TE (encompassing majors in engineering, construction, and computing), where women continue to be underrepresented. While public discourse mainly focuses on women's underrepresentation in STEM (science, technology, engineering, and math), we contend that STEM is an overly broad classification (see Kahn and Ginther, 2017, for a discussion on this). As Figure 1a demonstrates, women are not underrepresented in the science field, which in the Cine-UNESCO classification includes physical science, life science, math, and statistics. In fact, 52% of enrollees in science are women, contrasting sharply with just 25% of enrollees in TE. Figure 1b further highlights this point by presenting the distribution of female enrollees across programs in TE, science, and other fields. We observe that 84% of programs with fewer than a third of female enrollees are TE programs. The remaining 15% of male-dominated programs encompass various fields, with just 20% of them being in science.[11]

Earnings records are obtained from the unemployment insurance records of Chile's Ministry of Labor for the period between 2002 and 2019, which keeps track of the monetary contributions to the individual unemployment insurance account of each worker. We complement this data with records from the public sector for the 2018-2019 period. Our data covers almost the entire formal sector, excluding the self-employed.[12] Data from a nationally representative survey of Chilean households indicates that 9.5% of college graduates within our sample's age range are self-employed, with little variation across fields of study (see Appendix Table C.1). In the re-

[11]Of the 40 programs that are male-dominated and not TE, 8 are science programs, 8 are agriculture programs, 7 are programs in physical education teaching, and 5 are programs in music.

[12]The data also excludes workers with training contracts, workers under the age of 18, those in domestic service, and pensioners. However, individuals in our sample should not fall under these categories.

sults section we discuss how the lack of data on earnings for the self-employed might affect our interpretation of results.

Because we only have data on the public sector for the 2018-2019 period, our main specification focuses on average annual earnings in this period, when individuals in our sample are between 29 and 38 years old. Earnings records from the unemployment insurance are capped at roughly \$5,000 a month. In our sample, approximately 9.7% of men's and 3.3% of women's earnings reached this cap in 2018-2019. Enrolling in TE increase the probability of being in this cap by 1.25 p.p for men and 0.7 p.p for women. To deal with capped earnings, we follow Card et al. (2013) and use a series of Tobit models —fit separately by year, gender, and exam score decile —to stochastically impute the upper tail of the wage distribution. These Tobit models for a given year include worker's average earnings and topcoding rate in all other years. Using the estimated parameters from these models, we replace each censored wage value with a random draw from the upper tail of the appropriate conditional wage distribution.[13] In Appendix Table F.1 we show that our main results remain similar without this imputation.

Fertility and marriage records were obtained from the civil registration system in 2018. For each individual in our dataset, we were able to obtain marriage records and birth records for each of their offspring. We define two individuals as partners if they married or if they have a child who was registered at birth with both of them as parents. Under this definition, we identified a partner for 48% of individuals in our sample. However, we were only able to get information on partners' earnings, test scores and college enrollment if they signed up to take the PSU in or after 1999, which is the case for roughly 71% of partners.

Finally, we complement our administrative data with a survey that we designed and administered. The survey collected information about completed program, educational outcomes, preferences for different job characteristics, actual job characteristics, life and job satisfaction, and individuals' perception regarding cultural barriers and discrimination in the labor market. The survey was sent by email by 12 of the 25 institutions participating in the centralized system of admission to former students who enrolled between 2000 and 2008. We were able to collect in-

[13] Individuals who take the test more than once are assigned their last score. For individuals who are only observed in one year, we set the mean log wage in other years to the sample mean, and the fraction of censored wages in other years equal to the sample mean, and include a dummy in the model for those who are observed only once.

formation for 3,815 individuals. Because emails were sent directly by the institutions we do not know how many students received our survey. However, we estimate that approximately 180,000 students enrolled in these 12 institutions between 2000 and 2008, which implies a 2% response rate. Appendix Tables I.1 and I.2 show how the survey sample compares to our RD sample.

3.2 Sample

For any *target program* listed in an individual's application, our administrative data allows us to identify the *fallback program* where the applicant would be offered admission in case of marginally failing to get across the admission cutoff for the target program.[14] The sample we use for our main analyses includes applications in admission margins involving both TE and non-TE programs. This encompasses applications with a target program in TE and a fallback program in a non-TE field, as well as those with a target program in a non-TE field and a fallback program in TE.[15] The sample considers only applications to target programs that are oversubscribed (see Appendix D for more detail on how we build our main sample).

Naturally, this sample need not be representative of the population of applicants to higher education. First, we are considering marginal applicants, i.e., applicants with weighted scores near an admission cutoff, making our results local in nature (Lee and Lemieux, 2010). Second, we restrict our attention to oversubscribed programs. Since these programs are by definition more selective, we would expect applicants near the margin of admission for these programs to be academically and socially advantaged relative to the population of applicants.

Third, we consider applicants to programs in both TE and non-TE, which may differ from those applying to TE only. Our data show that 45% of students who apply to TE also submit applications for programs in other fields, while 55% exclusively apply within the TE domain. Women are

[14] We identify the fallback program as the most preferred program among those that are simultaneously i) less preferred and ii) less selective than the target program. Note that this need not be the program listed immediately below the target program, as that program may be more selective than the target program.

[15] The most common TE programs chosen by students in our sample are: civil engineering (12%), civil engineering in computer science and informatics (9%), industrial civil engineering (9%), food engineering (6%), computer science and engineering (5%), construction engineering (4%), biotechnology and bioengineering (3%), and industrial design (3%). The most common non-TE programs chosen by students in our sample are: business (14%), bachelor of science (7%), auditor accountant (6%), forestry engineering (6%), architecture (5%), agronomy (4%), pedagogy in mathematics and computer science (3%), aquaculture and fisheries engineering (3%), and science pedagogy (3%).

more likely than men to apply to both TE and other fields, whereas men are more likely to apply exclusively to TE programs. Appendix Table D.1 presents the socioeconomic characteristics and test scores across these different applicant groups: men and women who apply solely to TE, those who apply to both TE and alternative fields, and those who rank TE programs as either their target or fallback option. Overall, the different groups are quite similar in terms of their socioeconomic characteristics and test scores.

Table 1 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 1999-2007. As expected, the sample of students used in the analysis has a higher socioeconomic status and is more academically advantaged. These students have more educated parents, higher high school GPAs and perform much better in the language and math sections of the PSU. In terms of income, they report average annual earnings of $19,789 in 2018-2019, 53% above the average for all applicants. They are also less likely to have children (45% vs. 57%). Conditional on having children, they tend to have them at an older age (27.5 vs. 25.7 years old).

4 Empirical Strategy

To identify the causal effect of being admitted to a program in TE as opposed to a program in a different field, we focus on the sample of applicants who are near a margin of admission involving two programs, one in TE and one in a non-TE field. For applicants with a target program in TE and a fallback program in a different field, marginally crossing the admission cutoff for the TE program increases the probability of assignment to TE from 0 to 1. The opposite is true for applicants with a target program in a non-TE field and a fallback program in TE. Our main analyses pool both types of applicants. In addition to improving statistical power, this allows us to study the returns to majoring in TE, regardless of whether the program is more or less preferred, or more or less selective than the alternative.

Our empirical strategy rests on the assumption that applicants who are just below the admission cutoff for a given program have observable and unobservable baseline characteristics that are comparable in expectation to those of applicants who are just above the cutoff. Under this assumption, we are able to identify the causal effect of an admission offer to TE as opposed to non-TE by comparing the observed outcomes of applicants marginally assigned to TE to those of applicants marginally assigned to a non-TE field. This strategy is analogous to the one used in Kirkeboen et al. (2016).

Reduced-form Specification: Let s_{igjt} represent the weighted test score of individual i of gender g applying to target program j in year t. Given a program-year-specific admission cutoff c_{jt}, we can define the running variable $r_{igjt} = s_{igjt} - c_{jt}$. Admission to a program in TE by an applicant i of gender g applying to target program j in year t will be captured by an indicator variable TE^a_{igjt}. For applicants near the admission margin, this indicator depends on the running variable as follows:

$$TE^a_{igjt} = \begin{cases} 1(r_{igjt} \geq 0) & \text{if } j \in TE \\ 1(r_{igjt} < 0) & \text{if } j \notin TE, \end{cases} \tag{1}$$

Note that, because of how we build our sample, an applicant with a target program in TE necessarily has a fallback program in a non-TE field and vice-versa. In other words, for all applicants in our sample, $1 - TE^a_{igjt}$ is an indicator for admission into a non-TE program.[16]

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

$$y_{igjt} = \pi_{1g} \cdot r_{igjt} + \pi_{2g} \cdot (TE^a_{igjt} \times r_{igjt}) + \tau_g \cdot TE^a_{igjt} + \mu_{gjt} + \varepsilon_{igjt}, \tag{2}$$

where y_{igjt} is the outcome of interest for student i of gender g applying for admission in year t to target program j. Our parameter of interest, τ_g, represents the effect on applicants of gender g of a marginal admission offer into a program in TE as opposed to a non-TE program. The specification includes gender $\times$ target-program $\times$ application year fixed effects (μ_{gjt}) and slope parameters π_{1g} and π_{2g} which are allowed to vary by gender. Since all the parameters are gender-specific, our specification is analogous to having separate models for men and women.

Our specification differs from the traditional multi-cutoff RD designs in that our treatment indicator TE^a_{igjt} is not exactly a cutoff-crossing indicator. This is because getting across the cutoff

[16] These definitions only hold near the admission cutoff. A student with r_{igjt} considerably above zero might end up assigned to a more preferred program in a field different from that of the target program. Similarly, a student with r_{igjt} considerably below zero might end up assigned to a less preferred program in a field different from that of the fallback program.

and being assigned to the target program implies different things for applicants who have TE as their target program and those with TE as their fallback program. However, the logic of this specification is analogous to that of local linear regressions in standard settings, where the conditional expectation of each potential outcome (in our case, TE and non-TE) is approximated by linear functions of the running variable around the admission cutoff. In Section 5.2, we show that the results are very similar when we allow slopes to vary by whether TE is the target or fallback program, use quadratic polynomials, or include additional controls.

We estimate the reduced-form model by ordinary least squares using a triangular kernel around the cutoff, with bandwidths optimally selected following the covariate-adjusted procedure of Calonico et al. (2019). As discussed in Section 5.2, our main results are robust to alternative bandwidth choices, and point estimates remain stable over a wide range of bandwidths. Finally, since the same individual may be near the admission cutoff for more than one of their listed programs, we cluster standard errors at the individual level.

Second-stage Specification: Our main results are obtained from the following second-stage specification:

$$y_{igjt} = \delta_{1g} \cdot r_{igjt} + \delta_{2g} \cdot (TE^a_{igjt} \times r_{igjt}) + \beta_g \cdot TE^e_{igjt} + \xi_{gjt} + \varepsilon_{igjt} \tag{3}$$

This specification is analogous to the reduced-form specification, but uses applicant i's actual enrollment into the TE cutoff program, represented by the binary variable TE^e_{igjt}, rather than mere assignment to TE as the endogenous variable. The model is estimated by two-stage least squares, using assignment to TE, TE^a_{igjt}, as the instrument for TE^e_{igjt}, and weighting observations using a triangular kernel with the same optimally selected bandwidths used in the reduced-form estimation.

The purpose of this second-stage equation is to estimate the effects of actual enrollment in TE, as opposed to just receiving an admission offer to TE. The exclusion restriction requires an admission offer made to a TE program to affect outcomes only via its effect on the probability of enrollment in that program. Because of imperfect compliance, our estimates of β_g should be interpreted as local average treatment effects, i.e., the average effect of enrolling in TE among applicants of gender g who enroll in TE only upon receiving a marginal admission offer to a program in TE (Imbens and Angrist, 1994).[17]

4.1 Empirical Validation

To validate our empirical strategy, we perform conventional tests for regression discontinuity settings.

Manipulation checks. Because of the institutional setting and because students do not know ex-ante what the cutoff score will be for a given program, manipulation of admission test scores is highly implausible in this setting. Consistently, we find no evidence of manipulation when implementing the test suggested by Cattaneo et al. (2018) for men and women in our sample (see Appendix Figure E.1).

Continuity of covariates. To interpret our results as causal, there should be no discontinuities in potential confounders at the cutoff. Appendix Figure E.2 shows that this is the case for a rich set of demographic and socioeconomic characteristics including family size, parents' education, and parents' work status.

First Stage. For applicants in our TE vs. non-TE sample, crossing the admission cutoff for the target program induces discrete changes in enrollment in the TE. Figure 3 provides visual evidence of this compliance. When TE is the target program (Figure 3a), crossing the cutoff generates a sharp increase in the probability of enrolling in TE. Conversely, when TE is the fallback program, crossing the cutoff leads to a sharp decrease in this probability (Figure 3b). Figure 3c pools together these two samples using a common horizontal axis, where the running variable is re-defined so that positive values always indicate assignment to TE. Imperfect compliance revealed in these figures arise because some applicants decline the admission offer and either enroll in programs outside the centralized admission system or wait for the second round of admissions.

To quantify the effect of a marginal admission offer to TE on enrollment, we estimate first-stage regressions pooling applicants with TE as their target and fallback program. Specifically, we use the reduced-form specification in equation (2), with enrollment in TE as the dependent variable

[17] Non-compliance may arise from i) applicants who do not accept an admission offer to the TE program, or ii) applicants who, despite having received an admission offer to the non-TE program, end up enrolling in the TE program after the second round of admission. Interpretation of β_g as LATEs also requires to assume monotonicity, i.e., that a marginal admission offer to a given program cannot dissuade an applicant from enrolling in that program.

and assignment to TE as a regressor. Our first-stage estimates, reported in Panel A of Table 2, columns 1-2, indicate that marginal admission into TE increases the probability of enrolling in TE by 52 p.p. for men and 49 p.p. for women.

It is worth noting that although we use the probability of enrolling in the TE program during the admission year as the endogenous variable, this is very similar to the probability of ever enrolling in the TE program (i.e., enrolling in that program sometime between the application year and 2017). Very few individuals in our sample enroll in the TE program in subsequent years if they did not do so during the admission year. Specifically, being admitted into the TE program increases the probability of ever enrolling in that program by 50 p.p. for men and 48 p.p. for women. We choose to treat TE enrollment in the application year rather than ever TE enrollment as the endogenous variable because the latter might violate the exclusion restriction if the timing of enrollment affects outcomes for students who reapply and enroll in TE if they end up on the wrong side of the cutoff.

5 Empirical Results

5.1 Effects of majoring in TE

Reduced Form. We begin by examining the reduced-form effects of admission to TE on earnings and employment. Panel B of Table 2 reports these estimates separately for men and women for margins of admission involving a TE program and a non-TE alternative, shown in columns 1 and 2. For men, admission to TE increases annual earnings by $1,011 and the probability of having positive earnings in at least one month during 2018–2019 by 1.5 p.p.. In contrast, the corresponding reduced-form effects for women are small and statistically indistinguishable from zero.

Figure 4 provides a graphical representation of these reduced-form effects. Constructing this figure requires addressing two features of our setting. First, since we pool applicants for whom TE is the target program and those for whom it is the fallback, crossing the cutoff implies assignment to TE for the former and away from TE for the latter. We therefore redefine the running variable so that positive values always correspond to assignment to TE, regardless of applicant type. Second, because our specification controls for a linear function of the running variable and fixed effects, a standard binned scatter plot of the raw outcome would not recover the reduced-form estimate directly. We instead plot an adjusted outcome $\tilde{y}_{igjt}$ that removes the estimated contribution of the running variable and fixed effects from y_{igjt}, adding back a constant so that the level is interpretable. Because $\tilde{y}_{igjt}$ has been fully residualized with respect to the running variable, the fitted lines on each side of the cutoff are flat by construction, and the vertical discontinuity at the cutoff coincides exactly with the reduced-form estimate $\hat{\tau}_g$ reported in Table 2.[18]

Enrollment Effects. Panel C of Table 2 reports 2SLS estimates that translate the reduced-form effects into causal returns to enrolling in TE. For interpretation, the table also reports the mean outcomes of male and female compliers assigned to the non-TE program, which we estimate following Abadie et al. (2002).[19] Men and women in non-TE programs earn \$23,517 and \$18,655, respectively, which implies annual earnings of about \$30,661 and \$24,259 for those who worked at least one month. Enrollment in TE increases the earnings of men by \$1,954, representing a 8.3% increase relative to earnings in non-TE. In contrast, our estimates of this effect for women are small and statistically insignificant. Moreover, the returns to pursuing a major in TE are \$1,793 higher for men than for women (p-value = 0.0255).

Extensive Margin Effects. Part of the observed effects on earnings may be a result of effects on the extensive margin. The results in column 2 show that enrolling in TE increases the probability of men having positive earnings in at least one month during this period by 3 p.p., representing a 4% increase from the probability in non-TE (76.7%). We also observe positive effects on employment for women (1.8 p.p., or 2.3% relative to 76.9% in non-TE), although these effects are not statistically significant. In Table 3 we report estimates of the effects of enrolling in TE on other employment variables. We find positive effects for men and women on months employed, probability of having a permanent contract, accumulated experience and number of employers. Point estimates are smaller for women, but these gender differences are not statistically significant. Although we cannot reject the hypothesis that effects on employment are the same for men and women, a back-of-the-envelope calculation based on our point estimates suggests that about 20% of the gender gap in returns to TE could be attributed to gendered effects on employment.[20]

[18] See Appendix G for details on how these RD figures are constructed.

[19] We compute complier means by estimating a model analogous to the second-stage specification in equation (3), but using $(1 - TE^{e}_{igjt}) \cdot y_{igjt}$ as the outcome and $(1 - TE^{e}_{igjt})$ as the endogenous variable, instrumented by TE^{a}_{igjt}.

[20] From Table 2, the average earnings of female compliers in non-TE fields who worked at least one month in 2018-2019 are $\frac{\$18{,}655}{0.769} = \$24{,}259$. The observed effect of TE on female employment (0.018) implies an earnings effect purely from employment of $\$24{,}259 \times 0.018 = \$437$. Had women increased employment by as much as men (0.03),

Self-employment. Since we do not observe earnings for self-employed workers, our estimates on employment may include effects on the probability of self-employment. Data from a nationally representative survey of Chilean households shows that informality rates of college graduates in the same age range as the individuals in our sample is only about 9.5% and has little variation across fields. Moreover, the data suggests that incomes of self-employed graduates tend to be 20% lower compared to those working in the private or public sector (See Appendix C for further details). Given these patterns, we believe it is unlikely that self-employment is a significant source of bias in our results.

Heterogeneity by Alternative Field. The estimated effects of enrolling in TE on men's earnings are positive but modest. This is unsurprising given that 22% of students have science, 24% have business, and 11% have health as their alternative fields, all of which are relatively high-earning fields. The results shown in columns 3-8 of Table 2 indicate no earning gains for men of switching from business or health to TE, while switching from science to TE results in a 10% increase in earnings and a 4% increase in employment. The positive effect of enroling in TE mainly stems from the 43% of individuals transitioning from other, lower-earnings fields such as education, humanities, arts, or social sciences. Estimates for these men (columns 9 and 10), reveal that enrolling in TE increases their earnings by $4,133 (26%) annually and their employment by 5.4 p.p. (7.4%).

In contrast, women do not experience a positive return from enrolling in TE, regardless of their alternative field. Even among women switching from other, lower-earnings fields into TE, there is no observed effect on earnings. The return of pursuing a major in TE for men switching from other fields is $3,232 higher than for women (p-value = 0.008).

Effects over Time. Figure 5 allows us to appreciate how effects evolve over time. The figure displays model estimates for the evolution of mean earnings over time for men and women who enrolled in a non-TE program (blue lines), or in a TE program (red lines). The coefficients are estimated using the specification of equation (3), and allowing all the coefficients to vary by the number of years elapsed since high school graduation. Because we are using data on average

this would have been $\$24{,}259 \times 0.03 = \$728$. The difference of $291 ($\$728 - \$437$) represents 16% of the observed gender gap in returns to TE. Using men's earnings ($\frac{\$23{,}517}{0.767} = \$30{,}665$) the same exercise yields $368, or 21% of the gap.

earnings in 2018-2019, we only get to see each cohort at a specific age, and the figure is therefore capturing both dynamic effects (how effects evolve over time) and cohort effects. The plots suggest that men's earnings tend to grow steadily over time in both TE and non-TE fields. Consistent with our previous findings, we see that the red and blue lines start diverging 16 years after school graduation, reflecting a positive effect of enrolling in TE on men's earnings. In contrast, women's earnings grow slower over time, and there is no positive effect from enrolling in TE.

5.2 Robustness Checks

Alternative specifications and bandwidths: Appendix Table F.1 evaluates the sensitivity of our baseline estimates to a range of modeling choices (see also Appendix F for additional detail on the tested specifications). In addition to the baseline linear specification, we consider models that allow for quadratic polynomials in the running variable, include additional controls, and estimate more flexible specifications with four distinct slopes depending on whether TE is the target or fallback option. Across these specifications, the estimated returns to TE are very similar, indicating that our main findings are not sensitive to these choices. In addition, Appendix Figure F.1 shows that the results are robust to bandwidth selection, with point estimates remaining stable over a wide range of bandwidths.

Gender differences in program selection: Part of the gender differences in returns to TE fields may stem from men and women applying to different programs within both TE and non-TE fields. In our sample, men are more likely to apply to TE programs in construction, computing, and engineering, while women are more likely to apply to TE programs in industry and production (see Appendix Table F.2). These programs have different characteristics, raising the concern that majoring in TE might mean different things for men and women in our sample.

For instance, although majoring in TE leads applicants of both genders to programs with higher average graduate earnings, higher-scoring peers in math, and lower-scoring peers in language (all characteristics integral to what it means to major in TE), these effects are more pronounced for men (see columns 5–7 in Appendix Table F.3). While this does not affect the internal validity of our estimates, it may influence their interpretation.

To examine whether gender differences in program choices explain our finding of gendered returns to TE, we interpret our estimates through a standard Oaxaca–Blinder logic. Let (j,k) index the margin between a TE program j and a non-TE program k, and let β^g_{jk} denote the causal effect of enrolling in TE for applicants of gender $g \in \{m, f\}$ facing that margin. The average return to TE for gender g can then be written as

$$\beta^g = \sum_{j,k} \phi^g_{jk} \beta^g_{jk},$$

where ϕ^g_{jk} denotes the share of gender-g applicants in margin (j,k) among the TE–nonTE margins included in the analysis. Under this representation, gender differences in estimated TE returns can arise either because men and women experience different returns within the same margins, or because they are distributed differently across margins.

We quantify the role of differential sorting by re-estimating our baseline 2SLS specification after reweighting the data so that the distribution of application margins is held fixed. Specifically, when using men's distribution as the reference, we weight women's observations in margin (j,k) by n^m_{jk}/n^f_{jk}, where n^g_{jk} denotes the number of gender-g applicants in margin (j,k). Estimating the model on this weighted sample yields the counterfactual return

$$\beta^{f \to m} = \sum_{j,k} \phi^m_{jk} \beta^f_{jk},$$

which represents the average return to TE we would observe for women if they applied across margins in the same proportions as men. Appendix Table F.2 confirms that after reweighting, men and women are admitted to nearly the same sub-fields when admitted into TE.

This counterfactual allows us to decompose the gender gap in returns as

$$\beta^m - \beta^f = \underbrace{\left(\beta^m - \beta^{f \to m}\right)}_{\text{differential returns (men's weights)}} + \underbrace{\left(\beta^{f \to m} - \beta^f\right)}_{\text{sorting (women's returns)}}.$$

Our primary interest lies in the first term, which addresses the key question: what would happen if women attended the same programs as men? The estimates imply that $\beta^m - \beta^{f \to m} \approx \$2{,}173$ (see Appendix Table F.4), indicating that if women's program choices mirrored those of men, the gender gap in returns would be even larger than in the baseline estimates. Moreover, women's counterfactual return $\beta^{f\to m}$ remains close to zero and statistically insignificant. This implies that the sorting component evaluated at women's returns, $\beta^{f\to m} - \beta^{f}$, is small and slightly negative.

For completeness, we also consider the symmetric counterfactual that reweights men to match women's application margins, yielding $\beta^{m\to f}$. In this case, the implied return differential is $\beta^{m\to f} - \beta^{f} \approx \$844$, suggesting that men would continue to enjoy higher returns even under women's program distribution, although the magnitude of the gap would be smaller. This implies that men tend to attend programs that yield higher returns for them, consistent with the evidence in Appendix Table F.3.

Overall, we interpret these results as follows. While men and women do not attend exactly the same programs, even if women were to apply to the same programs as men, they would still not obtain positive returns from enrolling in TE. We therefore conclude that differential program selection is not driving the gender gap in returns to TE.

Effects on other program characteristics: A marginal admission offer to a TE program may affect characteristics of the attended program that are unrelated to field of study. For example, attending a TE program might mean enrolling in a program that is more or less preferred, closer to or further from home, or at a more or less selective institution. Such effects may potentially invalidate the interpretation of our estimates as returns to different fields of study.

For applicants with TE as their target program, assignment to TE goes hand in hand with assignment to a more preferred program. Conversely, for applicants with TE as their fallback program, assignment to TE entails assignment to a less preferred program. Appendix Table F.5 shows that assignment to TE affects the characteristics of the assigned program very differently depending on whether TE is ranked above or below the alternative, shifting peer composition, selectivity, and expected earnings in opposite directions across the two preference groups. By pooling applicants of both types, we eliminate any mechanical connection between enrolling in TE and enrolling in a more or less preferred program. In line with this, Appendix Table F.3 shows that, in our pooled sample, admission to TE has no effects on men's probability of being assigned to their target program or on the preference rank of their assigned program. For women, admission to TE entails assignment to slightly less preferred programs, but these effects are rather small.

Our pooling of both types of applicants also eliminates any mechanical connection between being accepted into TE and being accepted into a more selective choice. Appendix Table F.3 shows a relatively small negative effect on the probability of being accepted into an elite institution (either Universidad Católica or Universidad de Chile,) for both men and women (7 p.p. and 5 p.p., respectively) and a small negative effect on the probability of being accepted to a program outside their hometown region (2 p.p. and 3 p.p., respectively). To ensure that these effects are not driving our results, Appendix Table F.7 presents findings for a subsample of students choosing between TE and a different field within the same institution. The results remain consistent when the institution is held constant.

TE as target vs. TE as fallback:

While the pooled specification provides a useful benchmark for the average returns to TE, it may conceal meaningful heterogeneity across applicants with different relative field preferences. Table F.6 shows that the earnings returns to enrolling in TE are indeed heterogeneous for women along this dimension. Enrolling in TE has a negative earnings effect among women who rank TE above the alternative and a positive effect among those who rank TE below the alternative, with the difference between these two estimates being statistically significant. In contrast, for men the estimated returns to TE are similar across preference groups and do not display comparable heterogeneity. These findings are suggestive of a reverse-Roy pattern for women that runs counter to existing evidence showing that individuals tend to choose fields in which they have higher earnings returns (Kirkeboen et al., 2016).

One possibility is that this heterogeneity reflects systematic differences between applicants who rank TE above versus below the alternative, in ways that matter for labor market outcomes. These groups are similar in observable socioeconomic characteristics, although women who rank TE highest have slightly higher math performance on average (Appendix Table D.1,) a pattern that is unlikely to account on its own for their lower earnings returns in TE. Alternatively, the heterogeneity might emerge from systematic differences in the types of programs both types of applicants attend when they enroll in TE, as well as in the alternative programs they forgo. Appendix Table F.5 shows that assignment to TE shifts applicants into very different program environments depending on relative preferences. For women with TE as their target, marginal admission to TE entails enrollment in more selective and more competitive programs with higher-achieving peers, whereas for women with TE as their fallback, admission to TE leads to less selective programs with weaker peer environments. One possible interpretation is that the negative returns to TE for women who rank TE highest are concentrated in more selective and competitive TE programs, where competitive pressures may operate differently for men and women.

Gender differences in ability: Gendered returns to TE may be explained by differences in the 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 on individual sections of the test, or in terms of their high school GPAs. In fact, female students in our sample have slightly higher GPAs, and slightly lower math and language test scores than men. To test for this possibility, we re-estimate the earnings model using the same 2SLS specification but re-weighting the data so that the distribution of women's math scores mirrors that of men's math scores, and vice versa. Specifically, we divide the applicants into 18 equally spaced groups based on their math test scores. When using the distribution of male applicants, we weight women's observations by n_s^m/n_s^f, where n_s^g is the number of applicants of gender g in math score group s; conversely, when using the distribution of female applicants, we weight men's observations by n_s^f/n_s^m.

Appendix Table F.8 shows that the earnings estimates using the weighted sample are similar to those from the unweighted analysis, suggesting that our findings are not driven by gender differences in math scores. Specifically, we observe that even if the distribution of women's math scores mirrored that of men, they would still not experience a positive effect on earnings from enrolling in TE, regardless of the alternative field. Conversely, if men's math score distribution mirrored that of women, they would still experience a positive effect on earnings from enrolling in TE.

5.3 Effects of majoring in other fields

In this section, we contrast our previous results for TE with evidence on the effects of majoring in other high-earnings fields such as business or health, as well as in the mid-earnings field of science.

Panel A of Table 4 shows estimates of the returns to enrolling in business programs (which includes economics) relative to other fields.[21] We estimate that enrollment in a business program

[21] In our business sample, 56% of students choose a program in business and administration, and 23% choose a

increases men's earnings by \$1,289 and women's earnings by \$4,041, representing a 4.7% and 20.6% increase in baseline earnings, respectively, with the difference between these effects being statistically significant at 10% (p-value = 0.0654). In this sample, 50% of students have TE as an alternative and 42% have other, lower-earnings fields as an alternative, with very few individuals switching between science and business (1%) or health and business (7%). Our estimates for the effects of switching from TE to business mirror our previous findings on the effect of switching from business to TE. Specifically, we observe positive but statistically insignificant effects for both men and women when switching from TE to business. Although the point estimates are larger for women than for men, we cannot reject the hypothesis that the effects are the same for both genders.

Panel B of Table 4 shows analogous results for health programs.[22] Enrollment in health has positive effects on earnings for both men (\$3,011, representing a 13% increase) and women (\$1,732, representing a 9.3% increase), although the latter effect is statistically insignificant. In this sample, 26% of individuals have TE as an alternative, 34% have science as an alternative, and 37% have other fields as an alternative, with very few having business as an alternative. The results show positive effects of switching from science to health for both men and women, a positive but non-significant effect of switching from other, lower-earnings fields to health for men, and a positive and significant effect of switching from these fields to health for women. Across our different samples, we cannot reject the hypothesis that the estimates are the same for men and women.

Given the prominence of STEM in public discussions, we also examine the returns to enrolling in science and STEM fields, with STEM combining both science and TE. Panel A of Table 5 shows that majoring in science yields negative effects on earnings for both men and women, with no evidence of gendered returns. Consistent with this, estimates of the returns on enrolling in STEM programs (Panel B) show a null return for men and a negative return for women. This gender disparity in STEM can be attributed to the gendered returns observed in TE. While science yields negative returns for both genders, TE presents positive returns for men and no returns for women.

program in auditing and accounting. Universities in Chile do not offer programs in Economics, but most offer a program called *Commercial Engineering* that teaches both business administration and economics. A typical commercial engineer, must decide by their fourth year whether to major in business administration or economics. Only a small fraction of students choose economics and so we include these programs in our Business category.

[22] In our health sample, students choose programs in nursing (19%), chemistry and pharmacy (17%), medicine (11%), medical technology (11%), and nutrition (10%).

5.4 Explaining gender differences in returns to TE

The fact that we observe gendered returns in TE but not in other fields suggest that there might be something specific to TE that makes it profitable for men but not for women. In this section, we explore various potential explanations for the presence of gendered returns to TE, taking advantage of our data on graduation, firm and sector of employment, marriage, and fertility.

Graduation: Heterogeneous returns to TE for men and women could be a result of differences in graduation outcomes. Both men and women can have a hard time persisting in TE fields. Only a fraction of students who enroll in college expecting to major in a TE field actually finish one. This is not only due to students dropping out, but also to students switching from TE to non-TE fields.

Table 6 studies whether gender differences in graduation rates from TE can help explaining our main results. Because graduation outcomes are only available as of 2007, our analysis considers cohorts who graduated from high school between 2003 and 2007, who should not have graduated from a university prior to 2007. We find no significant effect of enrolling in a TE program on the probability of completing any university program. However, enrolling in TE does increase the number of years that students spend enrolled in college, by 0.18 for men and 0.1 for women (although this latter result is non-significant), and decreases the probability of graduating from any university program on time (i.e., within 6 years of high school graduation) by 5 p.p for men and 7 p.p for women. While students appear to spend more time in college as a consequence of enrolling in a TE program, we cannot reject the hypothesis that these effects are the same for men and women.

As we might expect, enrolling in TE increases the probability of graduating from a TE program for both men and women, by 36 p.p. and 38 p.p., respectively (see Appendix Figure H.1 for a visual representation of the reduced-form results on graduation.) The fraction is not zero for individuals who were initially admitted into a non-TE program because 18% of these men and 11% of these women eventually enroll and graduate from a TE program. Although being admitted into TE increases women's probability of graduating from the initially assigned TE program by a higher margin than men (33 p.p. as opposed to 28 p.p.), enrolling in TE increases the overall probability of graduating from any TE program by a similar amount for men and women, and we cannot reject that the estimates are the same.[23] Enrolling in TE also increases the number of years that both men and women spend enrolled in TE, by about 3.1 years for both men and women. Overall, our estimates suggest that differences in graduation are unlikely to explain gender differences in the returns to TE.

Firm and sector of employment: Gendered returns to TE may partly reflect differences in how men and women sort across firms and economic sectors once in the labor market. Alternatively, men and women may enter similar firms and sectors, but differ in the occupations they hold or in their subsequent career progression within those firms and sectors, leading to divergent earnings outcomes. To examine these possibilities, we study the effect of enrolling in TE on sector of employment and on the characteristics of firms where individuals work.

We find that enrolling in TE drives applicants away from sectors such as education and the public sector and toward manufacturing, construction, mining and quarrying, information and communication, and professional and scientific activities (see Table 7), all of which employ a high share of TE professionals.[24] Sectors where employment expands tend to be those where women are underrepresented, while sectors where employment contracts tend to be those where women are overrepresented. Although the overall pattern of sector reallocation induced by TE is similar for men and women, point estimates are often larger for men. In particular, men are more likely than women to enter male-dominated sectors after enrolling in TE. TE enrollment increases employment at sectors with fewer than one-third of women by 4.9 p.p. for men and 2.7 p.p. for women, a statistically significant difference.

We next examine the characteristics of employing firms. TE enrollment increases geographic mobility, raising the likelihood of working outside one's region or province of origin. Men who enroll in TE are 3.3 percentage points more likely to work in a different region from where they grew up, while women are 1.6 percentage points more likely to do so; we cannot reject equality

[23] It is unclear whether enrollment in TE affects outcomes for individuals who drop out or switch to a different field before completing their degrees in TE. If we believed that returns to TE materialize only for those who graduate from the field, then our main estimates would underestimate the returns to graduating from TE. Specifically, to obtain the returns to graduation from TE we would need to scale our 2SLS estimates by the inverse of the effect of TE enrollment on the probability of graduating from TE, which is 0.36 for men and 0.38 for women—implying scaling factors of 2.8 and 2.6, respectively.

[24] Among university graduates employed in these sectors, the share of TE graduates is 51% in manufacturing, 71% in construction, 34% in mining and quarrying, 41% in information and communication, and 36% in professional and scientific activities, compared to 16% in other sectors.

across genders. TE enrollment also increases exposure to male-dominated work environments. Men who enroll in TE are 10.7 percentage points more likely to work in a firm with fewer than one-third female employees, compared to 7.2 percentage points for women, a statistically significant difference. Similar patterns emerge for other measures of gender composition at both the firm and sector level. Thus, while men and women exhibit qualitatively similar sorting toward male-dominated environments, the magnitude of these shifts is typically larger for men.

Finally, TE enrollment affects the average earnings at the firms and sectors where individuals work. Average firm earnings (imputing zero for non-employment) increase by $1,143 for men and $601 for women; at the sector level, the corresponding increases are $1,059 and $700. Although gender differences in these estimates are not statistically significant, they are sizable relative to the overall gender gap in earnings returns to TE of $1,793. To assess the quantitative importance of these differences, we conduct a back-of-the-envelope accounting exercise using the point estimates. The gender difference in the effect on average firm earnings ($542) corresponds to roughly 30% of the overall gender gap, while the analogous difference at the sector level ($359) corresponds to about 20%. These figures combine differential employment responses and differential sorting among those employed. TE enrollment raises employment by 3.0 percentage points for men and 1.8 percentage points for women, though this difference is not statistically significant. Using baseline employment rates among compliers marginally rejected from TE, differential employment responses could mechanically account for about $240 of the firm-level difference (13% of the overall gap). Netting out this extensive-margin component leaves a residual difference of roughly $300 at the firm level, corresponding to about 17% of the overall gender gap.

Overall, although men and women display broadly similar sorting patterns across firms and sectors after enrolling in TE, differences in the magnitude of these responses—together with differential employment effects—may plausibly account for a non-trivial share of the gender gap in earnings returns. However, a substantial portion of the gap remains even after accounting for sectoral and firm-level reallocation and for extensive-margin responses, implying that men and women who sort into similar firms and sectors experience systematically different earnings outcomes, plausibly reflecting differences in occupational assignments or career progression within firms and sectors.

Fertility: Enrollment in a TE program may also influence fertility decisions. Such an impact on fertility could, in turn, affect earnings, particularly for women, as their earnings are typically more sensitive to childbearing.

Figure 6 shows model estimates of (i) the probability of having children and (ii) the total number of children, as functions of the number of years since high school graduation. These probabilities are shown for male and female compliers who enroll in a non-TE program (blue line) or in TE program (red line).[25] From this plot we conclude that fertility trends of women in TE fields are statistically indistinguishable from those of women in non-TE fields. Regardless of field of enrollment, the probability of having a child and number of children increase from nearly zero after one year out of high school to 67% and 1.1 children after 19 years. For men, we observe a small decline in the probability of having a child and number of children. Nineteen years out of high school, 60% of men have had a child and the total number of children equals 1.0. Enrolling in TE decreases the probability of having a child by 3 p.p. and the number of children by 0.06. Nonetheless, by 2018-2019, when we observe earnings, individuals in our sample are younger and these effects for men have not yet materialized (See Appendix Figure H.3)

Child penalty: Children pose a significant cost on the careers of women, something that has been documented by numerous studies.[26] More importantly for our purposes, these costs can vary across different occupations. For instance, Goldin (2014b) argues that women with children find it particularly hard to advance their careers in fields that disproportionally reward individuals who work long hours or work particular schedules.

In this section we study the extent to which the absence of returns to TE for women could be a consequence of the difficulties for women of making a career in TE compatible with childbearing. We begin by providing evidence on the child penalty for individuals who enrolled in either TE, science, business, health or other fields. Following Kleven et al. (2019b), Figure 7 uses an event

[25] Estimates are derived from building a panel where we observe each individual's fertility records from 1 to 19 years after high school. We then estimate equation 3 allowing all parameters to vary by the time elapsed since high school graduation. While we have data for every cohort up to 10 years after high school, we lose cohorts when examining longer time spans. Consequently, the estimates become noisier for individuals who have been out of high school for more years.

[26] See for instance: 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 (2014b); Adda et al. (2017); Angelov et al. (2016); Goldin and Katz (2016); Kleven et al. (2019b,a).

study around the birth of the first child to estimate the impact of children on the earnings of mothers and fathers who enrolled in TE, science, business, health or other fields in 2000-2008.[27] We define the child penalty as the average effect of having children on women relative to men across treated (non-negative) event times.[28] Our estimates focus on individuals who had their first child at least 7 years after graduating from high school and who were observed at least once before and once after birth. Each individual in our dataset is observed over an 18-year period, from 2002 to 2019. We track individuals for up to 14 years before and 12 years after the birth of their first child. However, due to the unbalanced nature of our panel, not all individuals are observed at every event time. Therefore, we focus on analyzing the short-run child penalty, defined as the average penalty from event 1 to 5.

Consistent with results from Kleven et al. (2019b), Figure 7 confirms the existence of a child penalty for women. Across fields of study, the earnings of men and women evolve similarly before parenthood —after adjusting for lifecycle and time trends— but diverge sharply after parenthood. Women experience a large drop in earnings after the birth of the first child, while men are essentially unaffected. The analysis reveals that the short-run child penalty differs substantially across fields of study. Women in TE face a 27% earnings penalty compared to 27% for women in science, 18% for women in business, 14% for women in health, and 15% for women in other fields. Notably, the penalties for women in TE are significantly different from those in other fields (except science) at the 99% confidence level. While these differences cannot be attributed directly to the field of study, as women who enroll in TE are likely to differ from those who enroll in other fields,

[27]The estimates in Figure 7 come from the following event study specification which is run separately for men and women in each field of study:

$$y_{ist}^{g} = \sum_{j \neq -1} \alpha_j^g \cdot \mathbb{1}(t = j) + \sum_k \beta_k^g \cdot \mathbb{1}(age_{is} = k) + \sum_y \gamma_y^g \cdot \mathbb{1}(y = s) + \varepsilon_{ist}^{g} \tag{4}$$

where y_{ist}^{g} is the outcome for individual i of gender g observed in year s and at event time t. For each parent in the data, event time t is indexed relative to the year of birth of the first child. The first term on the right-hand side includes event time dummies, the second term includes age dummies (to control for life-cycle trends), and the third term includes year dummies (to control for time trends). We omit the event time dummy at $t = -1$, implying that the event time coefficients measure the impact of children relative to the year just before the birth of the first child. We are able to identify the effects of all three sets of dummies because, conditional on age and year, there is variation in event time driven by variation in the age at which individuals have their first children.Kleven et al. (2019b) lay out the identification assumptions underlying this approach, compare its results to alternative approaches in the literature, and provide evidence of its ability to identify the causal effect of parenthood. We convert the estimated level effects into percentages by calculating $P_t^g \equiv \hat{\alpha}_t^g / E[\tilde{y}_{ist}^g | t]$ where $\tilde{y}_{ist}^g$ is the predicted outcome when omitting the contribution of the event dummies.

[28]Specifically, we define the short-run child penalty as $E[P_t^m - P_t^w | 0 < t < 5]$

they indicate that child penalties are stronger for women in TE.[29]

To assess whether these differences in child penalties are quantitatively relevant for the overall gender gap in returns to TE, we directly incorporate this mechanism into our RD framework. Specifically, we use the estimated child penalty associated with the field an individual attends as the outcome variable and estimate the 2SLS-RD effect of enrolling in TE on this outcome. This analysis shows that enrollment in TE increases the child penalty by 7.9 percentage points. To gauge the magnitude of this effect, we translate it into earnings units. Since 45% of women in our sample have children, this increase in the child penalty implies an average earnings reduction of approximately \$663 (calculated as $0.079 \times 0.45 \times \$18{,}655$, where \$18,655 is the mean annual earnings of non-TE female compliers), which represents about 37% of the overall gender gap in returns to TE. These results suggest that differential child penalties in TE constitute a quantitatively important channel that can contribute to the observed gender gap, even though enrollment in TE does not affect women's fertility.

Marriage: Enrolling in a TE program may also impact marriage outcomes. On the one hand, majoring in TE alters the characteristics of peers at an age when many form relationships. On the other hand, it could enhance an individual's appeal as a partner, signaling quality or higher expected earnings. Any effect on marriage market outcomes could in turn have an effect on earnings, particularly for women, as their labor supply is likely to be affected by their spouse's wage.

Table 8 studies effects of enrolling in TE on marriage market outcomes. By 2018, almost half of the individuals in our sample have a child, and a quarter are married. For women, enrolling in TE does not significantly affect the probability of having a child or being married (columns 1 and 2). For men, enrolling in TE does not affect the probability of having a child by 2018 but decreases the probability of being married by 2 p.p.[30,31]

Based on this information we identify two individuals as partners if they married or if they have a child that was registered with both of them as parents. Using this definition, almost half of the

[29] Figure 7 does not show point estimates for women on the year the child is born because we are unable to separate earnings from maternity leave benefits and these estimates are misleading.

[30] We report the average probability of having a child for men and women in 2018 when they are between 29 and 37 years old. While we find a slight decrease in the probability of having a child for men over 34, this result equals zero when we average estimates for men between 29 and 37 years old.

[31] See Appendix Figure H.3 for a visual representation of the reduced-form results on the probability of being married in 2018-2019.

individuals in our sample have a partner. Enrolling in TE does not affect the probability of having a partner (column 3). However, we can only obtain information on partners' earnings, admission test scores, and enrollment if they are in our records (i.e., if they signed up for the standardized admission test in or after 1999). Column 4 shows that we can gather information on partners for 37% of men and 33% of women who do not enroll in TE. Also, enrolling in TE does not affect the probability of obtaining information on a partner.

Columns 5-9 study the effects of enrollment in TE on the characteristics of partners for whom we could get information.[32] Results show that women who enroll in TE tend to partner with individuals who have higher math and language scores. Although they are not more likely to partner with someone from the specific program where they were admitted (column 7), they increase their probability of partnering with someone who enrolled in a different TE program by 11 p.p., representing a 69% increase over baseline probabilities (column 8).[33] For men, we find little differences in partner characteristics. Compared to men in non-TE fields, men in TE partner with women who have slightly lower language scores but similar math scores. They are 3 p.p. less likely to partner with someone from their specific program but 3 p.p. more likely to partner with a woman who enrolled in TE at a different institution, resulting in no net effect on the overall probability of partnering with a woman who studied TE.

We also find some evidence that women who enroll in TE partner with higher-earning individuals. The point estimates imply that their partners' annual earnings are about $2,500 higher on average, although this effect is not statistically significant. In standard household labor supply models, higher spousal earnings reduce an individual's labor supply, particularly for women, providing a plausible channel through which marriage-market outcomes may affect observed earnings. Although noisily estimated, the magnitude of this marriage-market return for women is comparable to the labor-market return to TE observed for men, suggesting that TE enrollment may generate economically meaningful returns for women outside the labor market. In contrast, we find no effect

[32] Although this analysis cannot be strictly interpreted as causal, the fact that enrolling in TE does not affect the probability that we observe partners' information makes us more confident of the value of these analyses.

[33] Unfortunately, we only have enrollment and graduation records for the entire system starting from 2007, which prevents us from determining whether an individual's partner ever graduated from or enrolled in a TE program. However, we do have complete records (as of 2000) for the centralized admission system. This allows us to analyze the effects on the probability of having a partner who ever enrolled in the TE cutoff program or another TE program within the centralized admission system.

of enrolling in TE on men's partners' earnings.[34]

Our results on marriage should be interpreted with caution, as we are unable to obtain educational and earnings records for every partner in our sample. Nonetheless, our findings suggest that enrollment in TE may yield positive long-term returns for women in the marriage market. Women who enroll in TE are more likely to partner with TE enrollees, who are typically well paid, and with individuals who have higher math and language scores. We also find suggestive evidence that their partners have higher earnings at the time of observation, although these estimates are based on earnings measured relatively early in the life cycle and should therefore be interpreted cautiously. Taken together, these patterns point to an economically meaningful marriage-market channel through which TE enrollment may shape women's outcomes, even if these effects do not fully materialize in women's own labor-market earnings.

5.5 Survey evidence

In this section, we present results from a survey we administered to former college students. The survey gathered information on individual variables not observable in our administrative data, such as preferences for job attributes, actual job characteristics, satisfaction with chosen profession, and perceived discrimination. This rich information may help interpret our causal results. The survey has a low response rate and respondents are unlikely to be fully representative of the population of applicants in our administrative data, despite being similar along some observable dimensions (Appendix Tables I.1 and I.2). The survey evidence is therefore best viewed as complementary to the causal analysis in earlier sections, offering descriptive insights into workplace experiences and perceived barriers that may contribute to the observed patterns alongside other mechanisms studied in the paper.

Table 9 describes respondents' employment status, job attribute preferences, and actual job attributes. The table shows mean values by gender and field of study (columns 1-12), as well as two key comparisons: the gender gap within TE (column 13) and the difference between women in TE versus women in non-TE fields (column 14). According to the survey data, 78% of respondents

[34]We only have information on partners' earnings up to 2017, which is why our measure of annual earnings uses the average annual earnings of partners in 2016-2017. This measure does not include earnings from the public sector.

work for a company, 13% are self-employed, and 9% are unemployed, aligning with rates observed in a nationally representative survey (see Appendix C). Regarding job preferences, female respondents show significantly stronger preferences than male respondents for workplace flexibility (52% vs. 48%), fixed salary (55% vs. 40%), work-life balance (86% vs. 77%), socially impactful work (72% vs. 57%), interpersonal job roles (45% vs. 31%), proximity to home (41% vs. 33%), and same-sex co-workers (20% vs. 4%). Conversely, women exhibit significantly lower preferences for high earnings (16% vs. 19%) and career advancement opportunities (38% vs. 46%). All these differences are statistically significant at least at the 5% level.

Gender differences in job attribute preferences have been well-documented in the literature (see Cortes and Pan, 2018 for a review).[35] Our survey results contribute novel findings on women's preference for same-sex coworkers and how preferences vary across fields of study. Notably, women in TE fields show significantly lower preferences for fixed salary, work-life balance, socially impactful work, and interpersonal job roles, but significantly stronger preferences for career advancement opportunities compared to women in other fields (column 14). As a result of these distinctive preferences, when comparing men and women within TE, gender gaps in preferences are considerably attenuated for work-life balance, interpersonal contact, and career advancement relative to the gender gaps observed in the general population. Nevertheless, significant gender differences persist within TE for other job attributes such as fixed salary, same-sex coworkers, and job proximity to home (column 13).

If gender differences in job preferences were the primary driver of variation in returns to pursuing TE programs, we would expect women in TE to be more likely than men to hold jobs with their preferred attributes. However, our survey data reveals this is not the case for most attributes (column 13). Women in TE are significantly more likely than men to have fixed salaries (66% vs. 53%) and less likely to work in male-dominated firms (44% vs. 52%), which aligns with their stated preferences. However, contrary to preferences, women in TE are significantly less likely than men to have jobs offering schedule and location flexibility (30% vs. 41%). Differences in

[35]Previous studies have found that women tend to be more risk-averse and less competitive than men (see surveys by Marianne, 2011 and Azmat and Petrongolo, 2014), place greater value on working with people and being socially useful (Fortin, 2008; Grove et al., 2011; Pinker, 2009; Pischke and Lordan, 2021), and prioritize workplace flexibility, particularly after childbirth (Flabbi and Moro, 2012; Wiswall and Zafar, 2018; Pertold-Gebicka et al., 2016; Herr and Wolfram, 2012; Cha, 2013; Wasserman, 2015; Cortes and Pan, 2016).

other job attributes—such as work-life balance (31% vs. 34%), opportunities to help others or be useful to society (39% vs. 34%), interpersonal contact (36% vs. 33%), and proximity to home (33% vs. 35%)—are not statistically significant, though the direction often also runs counter to women's stated preferences. These findings align with other studies reporting that women are less likely to have flexible work arrangements, despite expressing a higher preference for such flexibility (Mas and Pallais, 2020).

Table 10 describes career satisfaction, perceived barriers and experiences of discrimination, and follows the same structure as Table 9. Women in TE express lower levels of professional satisfaction compared to men in TE. For example, only 32% of women in TE strongly agree that their profession motivates and excites them, compared to 43% of men. Similarly, fewer women strongly agree that they chose a profession aligned with their abilities (45% vs. 52%) or that their profession has allowed them to develop professionally (39% vs. 52%). All these differences are statistically significant (column 13).

Family-related obstacles are prevalent across fields of study and show large gender gaps. For instance, 42% of women agree that taking care of their family has hindered their professional development, whereas this is the case for only 18% of men. Additionally, 55% of women agree that having more responsibilities at work has had a negative effect on their family life, compared to 43% of men.

Importantly, our survey suggests that gender discrimination is more prevalent in TE than in other fields. Among women in TE, 50% agree or strongly agree that their gender has negatively impacted their job search process, and 49% agree that their family has hindered their career development—both significantly above the rates for men in TE and women in other disciplines (columns 13 and 14). This pattern extends to workplace experiences: women in TE report discrimination rates of 66% in promotion, 72% in decision-making opportunities, 77% in earnings, 45% in job evaluation, 58% in developmental opportunities, and 60% in task assignment. These figures are significantly higher than those reported by men in TE across all dimensions (column 13) and exceed the rates reported by women in other fields, with most differences being statistically significant (column 14). Despite facing these substantial barriers, 51% of women in TE agree that they are willing to make sacrifices to reach high-level positions—a rate statistically indistinguishable from the 53% of men in TE and substantially higher than the 39% of women in other fields. This suggests that women who pursue TE careers exhibit ambition levels comparable to their male counterparts, yet face significantly greater obstacles in achieving their professional goals.

6 Conclusion

Exploiting an institutional setting that generates quasi-random assignment of applicants into different fields of study, we document substantial gender differences in the economic returns to majoring in Technology and Engineering (TE). While men experience large and persistent earnings gains from pursuing TE majors, women do not, even when compared to graduates from traditionally lower-paying fields. These gendered returns appear specific to TE and do not extend to other high-earning fields such as business or health, where men and women obtain positive and broadly similar returns.

We investigate several potential explanations for this gap. Differences in graduation outcomes and fertility decisions do not account for the absence of returns for women. We also find that TE enrollment induces broadly similar patterns of sorting across firms and sectors for men and women, shifting both toward higher-paying and more male-dominated work environments, although these reallocations tend to be larger for men. An accounting exercise suggests that such sorting differences—together with differential employment responses—can explain only a limited share of the overall gender gap in returns. As a result, a substantial portion of the gap remains even among individuals who work in similar firms and sectors, pointing to differences in occupational roles or career advancement within those workplaces. In line with this pattern, descriptive evidence from a survey we collected indicates that women who majored in TE—despite reporting strong career orientation—are more likely to report workplace discrimination than men and than women in other fields.

Consistent with the possibility that women face barriers within TE work environments, we document that the earnings penalty associated with childbearing is substantially larger for women in TE than in other fields. Using event-study evidence around the birth of the first child, we show that motherhood leads to sharper and more persistent earnings declines in TE than in business, health, or other fields. Enrollment in TE increases exposure to these penalties, and a simple accounting exercise indicates that differential child-related earnings penalties may represent a quantitatively important component of the overall gender gap in returns to TE.

Finally, we present suggestive evidence that women who enroll in TE tend to partner with higher-earning spouses. Although these estimates are noisy and not statistically significant, their magnitude is economically meaningful and consistent with standard household labor-supply mechanisms through which higher partner earnings may reduce women's labor supply and observed earnings.

Our findings have important implications for policies aimed at increasing women's participation in STEM fields. Our results caution against initiatives that focus solely on encouraging women to enter these majors without addressing the subsequent challenges they face in the labor market. Effectively closing gender gaps also requires efforts by policymakers and employers to create more inclusive and supportive work environments in TE-aligned jobs, including addressing the career costs associated with childbearing.

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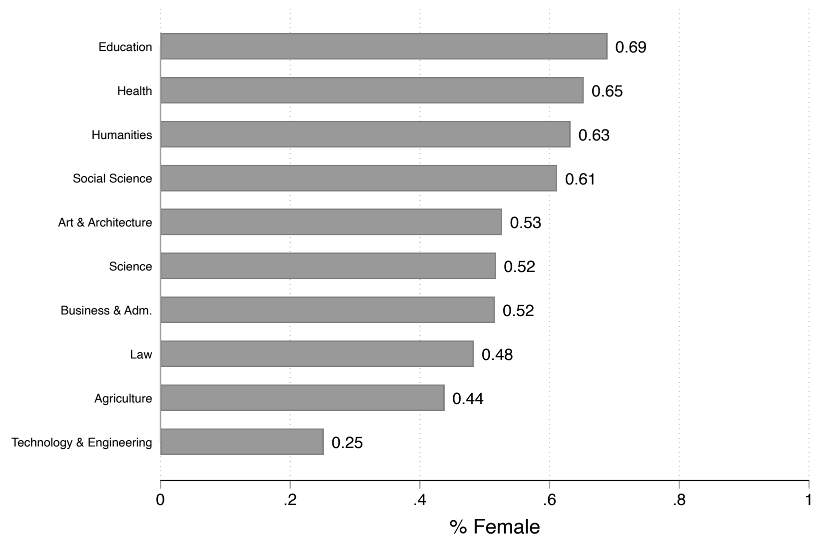
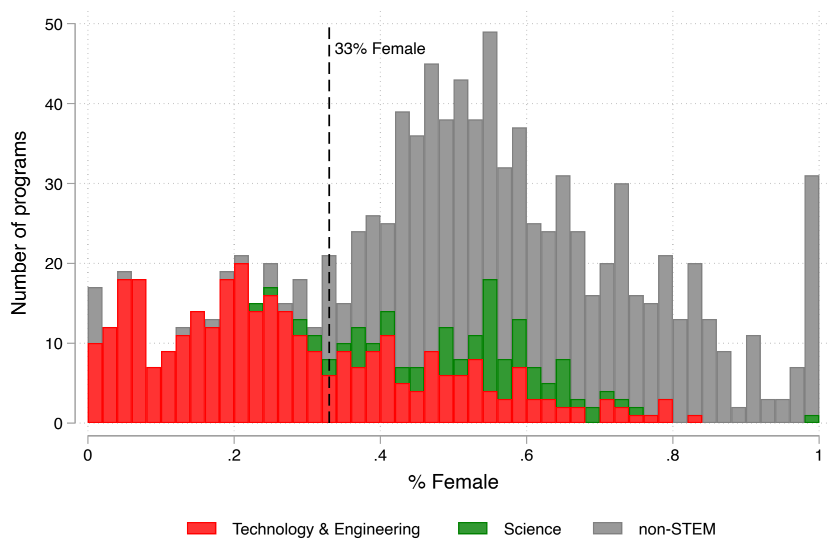
Figures and Tables

Figure 1: Gender Composition of Fields



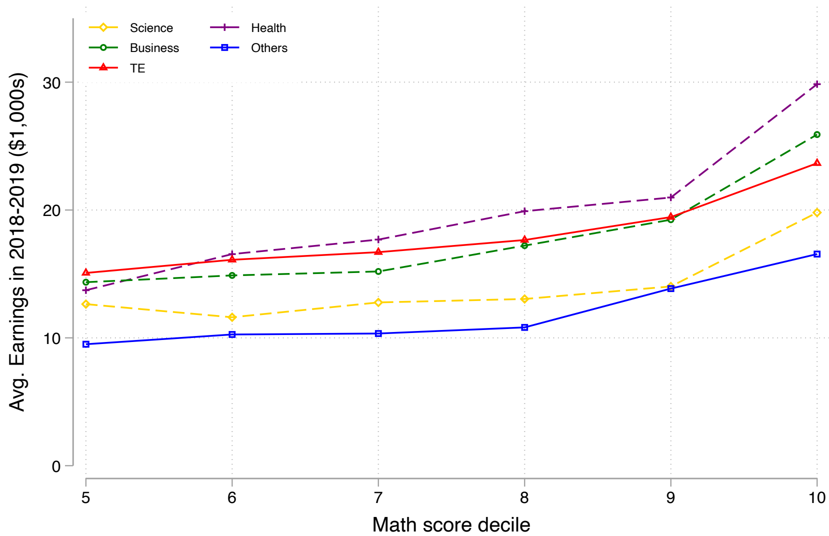
(a) Percentage of female enrollees by field



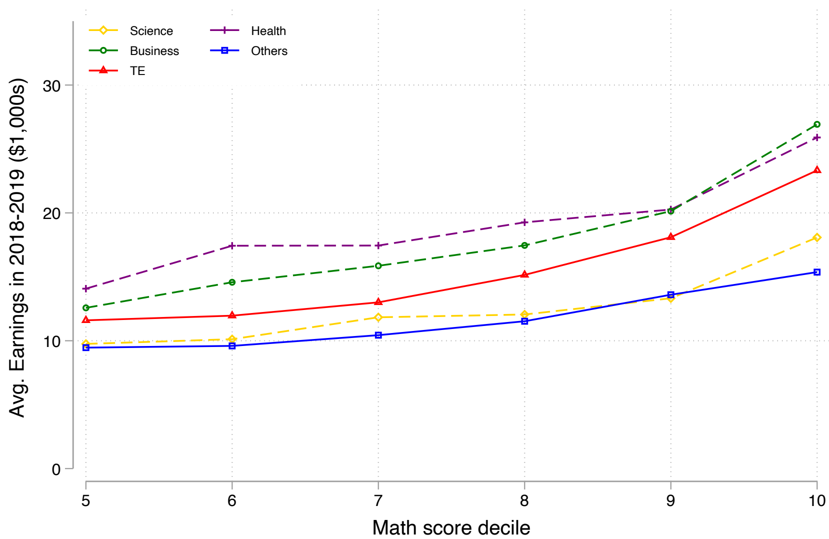
(b) Program distribution by % of female enrollees and field

Notes: Plot (a) shows the fraction of first-year enrollees who are female by field of study, averaged through cohorts enrolling between 2000 and 2008 – the same cohorts we consider in our earnings analysis. Plot (b) shows the distribution of programs in TE, science and non-STEM fields by the average percentage of female students enrolled between 2000 and 2008.

Figure 2: Annual Earnings in 2018-2019 for Men and Women by Field of Study & Academic Performance



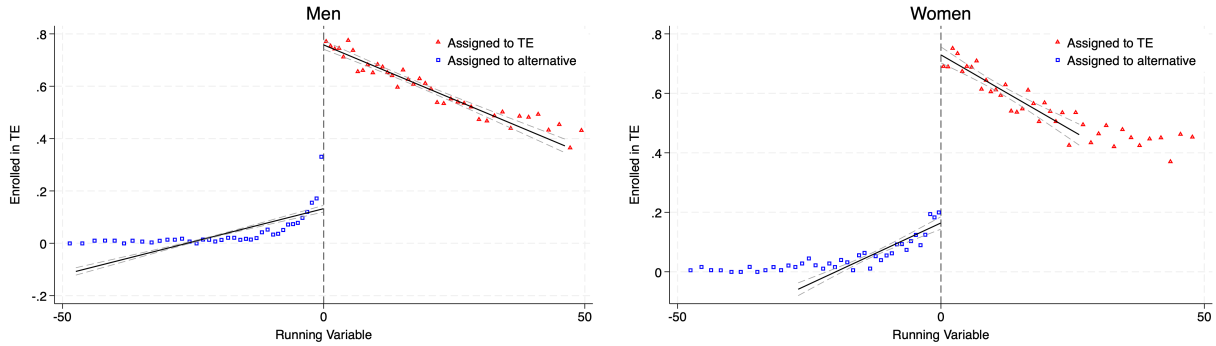
(a) Men



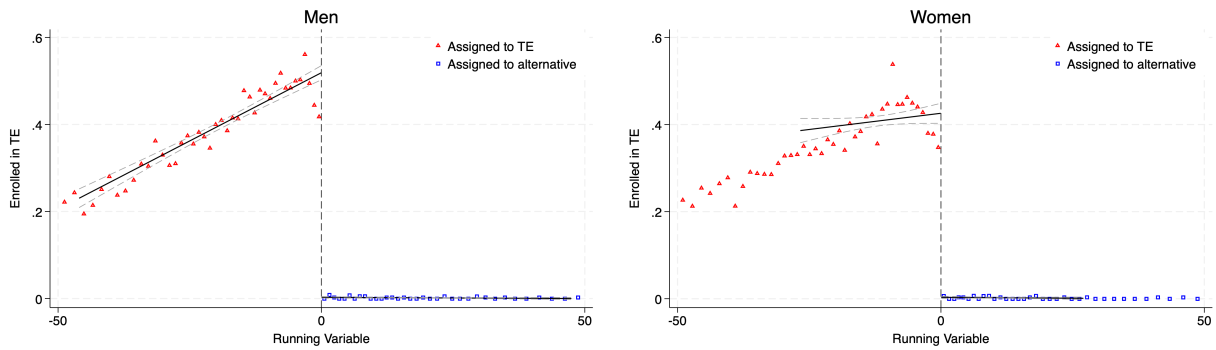
(b) Women

Notes: This figure shows average annual earnings in 2018-2019 (including 0 earnings for the unemployed) for (a) men and (b) women who enrolled in each field between 2000 and 2008, at different deciles of math test scores

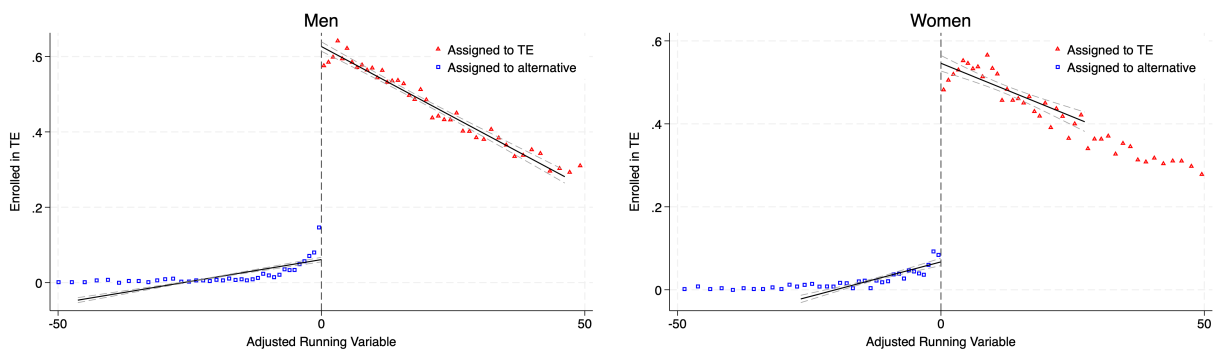
Figure 3: First Stage



(a) TE as target program



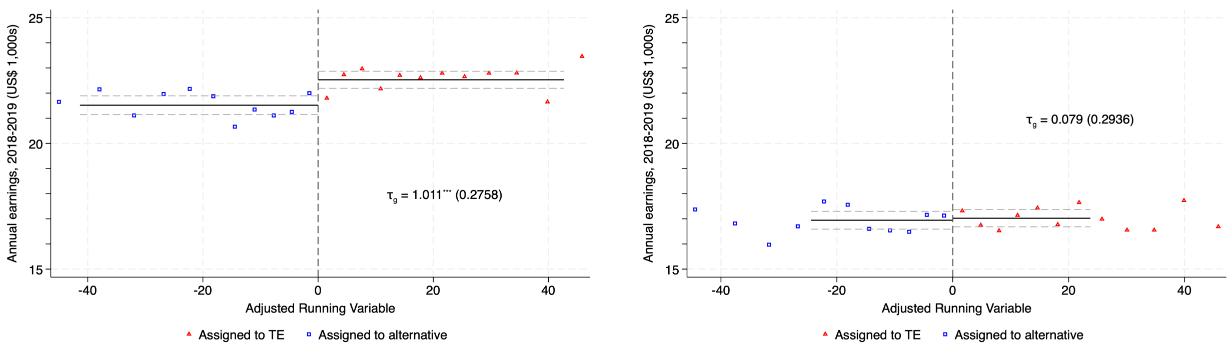
(b) TE as fallback program



(c) Pooled sample

Notes: This figure shows how crossing the admission cutoff affects the probability of enrolling in a TE program in the application year, separately for men (left-hand panels) and women (right-hand panels). Panel (a) corresponds to applicants with TE as their target program, panel (b) to applicants with TE as their fallback program, and panel (c) pools both types of applicants. In panels (a) and (b), the horizontal axis measures the difference between the applicant's test score and the admission cutoff for the target program, $r_{igjt} = s_{igjt} - c_{jt}$, so that applicants with $r_{igjt} > 0$ are offered admission to their target programs. In panel (c), the horizontal axis is an adjusted running variable R_{igjt}, defined as r_{igjt} when the target program is in TE and as $-r_{igjt}$ when the target is non-TE and the fallback program is in TE. With this definition, applicants with $R_{igjt} > 0$ are offered admission to a TE program. Dots represent mean enrollment outcomes in equally spaced, non-overlapping bins. Solid black lines show linear fits on each side of the cutoff, with dashed lines indicating 95% confidence intervals; fits are estimated using observations within the optimally selected bandwidth around the cutoff.

Figure 4: Effects of Assignment to TE on Annual Earnings, 2018-2019

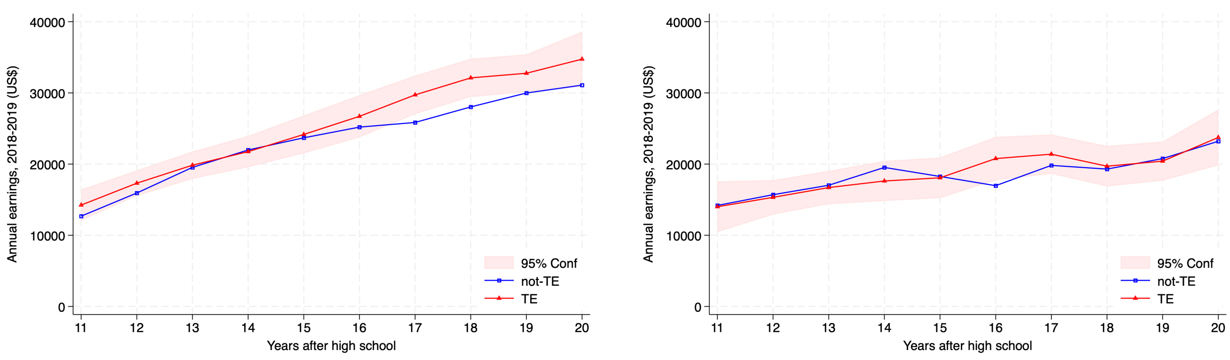


(a) Men

(b) Women

This figure shows, for (a) men and (b) women, the reduced-form effect of assignment to TE on mean annual earnings in 2018–2019. The running variable is adjusted so that values to the right of the cutoff correspond to assignment to TE for all applicants. Dots represent average values of an adjusted outcome, constructed by removing the contribution of test scores, covariates, and fixed effects implied by the reduced-form specification in equation (2), estimated on the pooled sample using observations within the optimally selected bandwidth around the cutoff. This adjustment ensures that the figure visualizes the same object identified by the regression model. Solid lines and confidence intervals then summarize the adjusted outcome on each side of the cutoff, imposing flatness so that the visual discontinuity corresponds exactly to the reduced-form estimate.

Figure 5: Effect of Enrollment in TE on Annual Earnings over Time

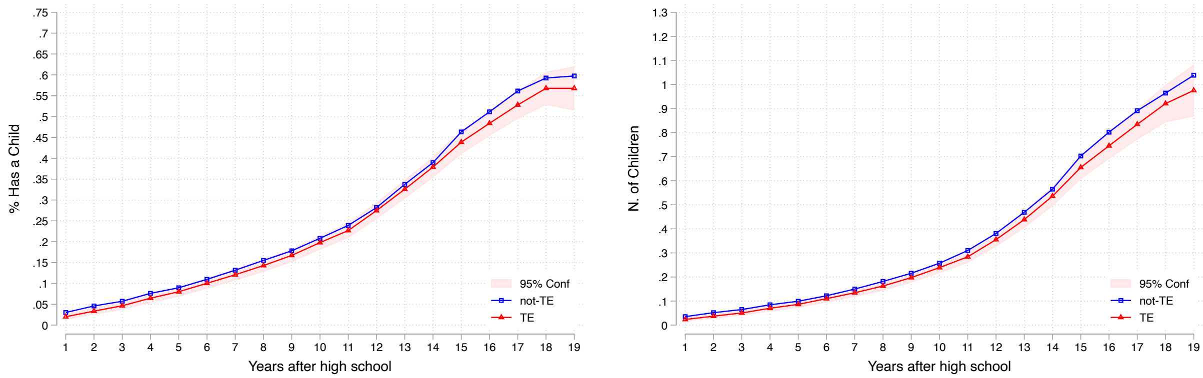


(a) Men

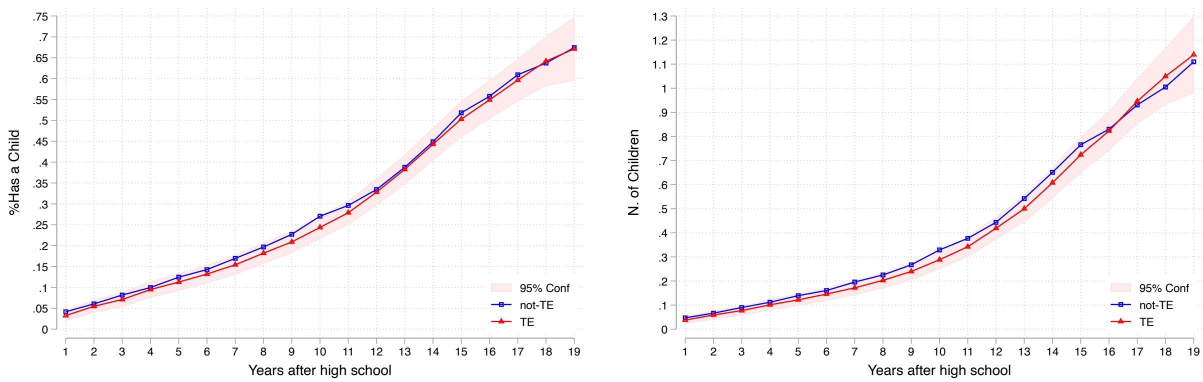
(b) Women

Notes: This figure shows for men (a) and women (b) model estimates of annual earnings in 2018-2019, 11 to 20 years after high school for compliers in the margin of receiving an admission offer into either TE or non-TE and who, i) enrolled in TE (red line), or ii) enrolled in non-TE (blue line). The difference between the red and the blue line represents the estimated causal effect of enrolling in TE as opposed to non-TE. The red shadows show 95% confidence intervals. We estimated separate regressions for individuals at each year since high school graduation.

Figure 6: Effect of Enrollment in a TE on Fertility over Time



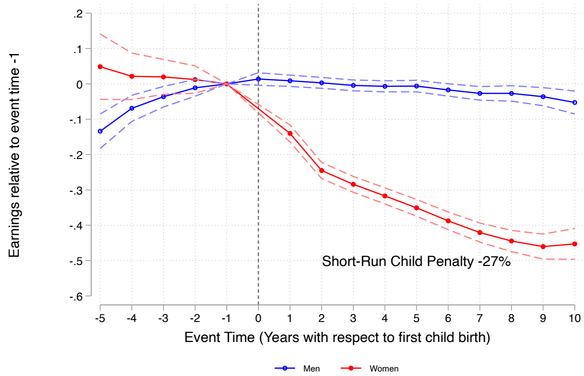
(a) Men



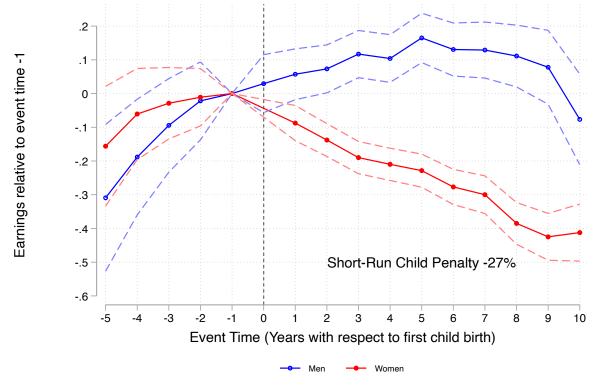
(b) Women

Notes: This figure shows for men (a) and women (b) model estimates of the probability of having a child (on the left), and the mean number of children (on the right), 1 to 19 years after high school for compliers in the margin of receiving an admission offer into either TE or non-TE and who, i) enrolled in TE (red line), or ii) enrolled in a different field (blue line). The difference between the red and the blue line represents the estimated causal effect of enrolling in TE as opposed to non-TE. The red shadows show 95% confidence intervals. We estimated separate regressions for individuals at each year since high school graduation.

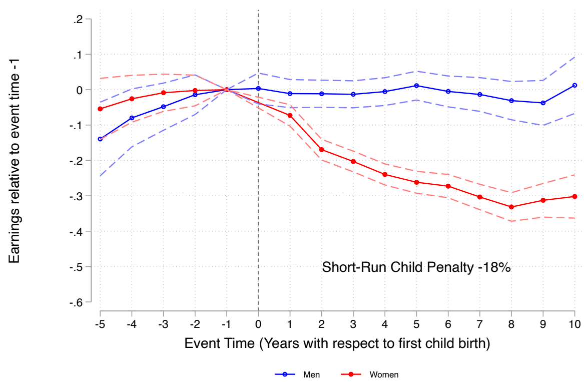
Figure 7: Child Penalty by Field of Study



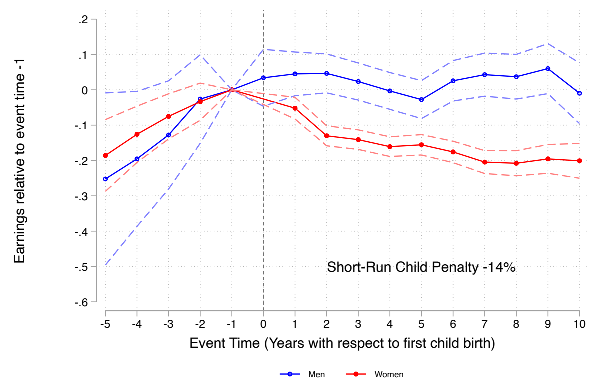
(a) TE



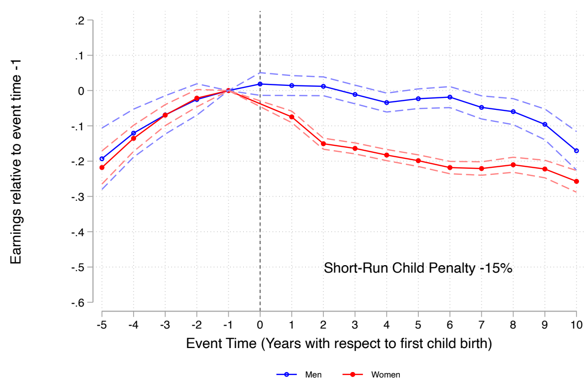
(b) Science



(c) Business



(d) Health



(e) Others

Notes: This figure shows event time coefficients estimated from equation (4) as a percentage of the counterfactual outcome absent children (i.e.,$P_t^g \equiv \hat{\alpha}_t^g / E[\tilde{Y}_{ist}^g|t]$ as defined in section 5.4) for men and women who enroll in different fields of study. Discontinuous lines show 95% confidence intervals. Each figure also displays the average child penalty over event times 0-5 defined as $E[P_t^m - P_t^w | 0 < t < 5]$. All of these statistics are estimated on a sample of parents who had their first child at least 7 years after graduating from high school and who are observed at least once before and once after birth. Every individual in our data is observed for 18 years (between 2002 and 2019). Individuals are observed up to 14 years before and 12 years after the birth of their first child. The effects on earnings are estimated unconditional on employment status. We do not show point estimates for women on the year the child is born because we are unable to separate earnings from maternity leave benefits and these estimates are misleading.

Table 1: Descriptive Statistics

	All			Sample		
	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Socioeconomic Characteristics						
Female	0.527	0.000	1.000	0.349	0.000	1.000
Lives in the capital	0.427	0.433	0.422	0.371	0.379	0.356
Total HH members	4.533	4.477	4.583	4.538	4.539	4.538
	(1.793)	(1.801)	(1.784)	(1.641)	(1.668)	(1.588)
Total HH members work	1.292	1.320	1.268	1.271	1.292	1.232
	(0.772)	(0.792)	(0.752)	(0.712)	(0.729)	(0.678)
Head of HH father	0.673	0.691	0.656	0.717	0.727	0.699
Head of HH mother	0.234	0.224	0.243	0.223	0.216	0.237
Mother primary ed	0.232	0.213	0.249	0.131	0.130	0.133
Mother secondary ed	0.501	0.511	0.492	0.486	0.478	0.500
Mother tertiary ed	0.267	0.276	0.258	0.383	0.392	0.367
Father primary ed	0.219	0.200	0.236	0.125	0.120	0.133
Father secondary ed	0.457	0.461	0.453	0.413	0.407	0.426
Father tertiary ed	0.324	0.339	0.311	0.462	0.473	0.442
Father works full-time	0.681	0.704	0.661	0.714	0.727	0.690
Father works part-time	0.127	0.116	0.136	0.110	0.103	0.122
Mother works full-time	0.336	0.346	0.328	0.373	0.378	0.365
Mother works part-time	0.062	0.061	0.063	0.053	0.054	0.051
Academic Performance						
GPA	5.628	5.554	5.693	5.927	5.870	6.033
	(0.501)	(0.500)	(0.492)	(0.443)	(0.453)	(0.403)
Language Score Percentile	46.689	47.972	45.549	68.335	69.477	66.211
	(28.984)	(29.341)	(28.616)	(21.465)	(21.635)	(20.980)
Math Score Percentile	46.629	51.088	42.668	74.807	76.919	70.879
	(28.965)	(29.125)	(28.238)	(19.051)	(18.624)	(19.214)
Earnings & Employment						
Employed (2018-2019)	0.685	0.713	0.660	0,768	0.771	0.760
Annual Earnings (2018-2019)	12,936	14,947	11,148	19,789	21,433	16,711
	(16,838)	(19,227)	(14,145)	(23,737)	(25,930)	(18,572)
Marriage and Fertility						
Has Children	0.567	0.506	0.622	0.454	0.432	0.496
N of Children	0.933	0.818	1.034	0.704	0.671	0.765
	(1.005)	(0.983)	(1.013)	(0.912)	(0.909)	(0.916)
Age at First Birth	25.745	26.583	25.141	27.533	27.906	26.928
	(4.921)	(4.843)	(4.888)	(4.898)	(4.835)	(4.939)
Obs	1,360,283	643,848	716,435	57,124	37,238	19,886

Notes: This table shows descriptive statistics for applicants in our sample of analysis (columns 4-5) and for everyone who signed up for taking the admission test between 1999 and 2007 (columns 1-3.). Standard deviations are reported in parentheses.

Table 2: Effects of Enrollment in TE on Earnings and Employment in 2018-2019

	Alternative Field									
	All non-TE 100%		Science & Math 22%		Business 24%		Health 11%		Other non-TE 43%	
	earnings (1)	employment (2)	earnings (3)	employment (4)	earnings (5)	employment (6)	earnings (7)	employment (8)	earnings (9)	employment (10)
Panel A: First Stage										
First stage - Men	0.518***	0.518***	0.624***	0.624***	0.508***	0.508***	0.560***	0.560***	0.478***	0.478***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
First stage - Women	0.490***	0.490***	0.561***	0.561***	0.442***	0.442***	0.479***	0.479***	0.438***	0.438***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Panel B: Reduced Form										
Admitted to TE - Men	1,011***	0.015***	1,671**	0.019*	−263.1	0.004	−1,385	−0.004	1,974***	0.026***
	(275.8)	(0.00)	(694.0)	(0.01)	(637.5)	(0.01)	(1,500)	(0.02)	(392.2)	(0.01)
Admitted to TE - Women	78.86	0.009	915.3	0.022	−725.3	0.013	903.9	−0.010	394.3	−0.001
	(293.6)	(0.01)	(600.8)	(0.01)	(533.2)	(0.01)	(1,033)	(0.02)	(396.6)	(0.01)
Panel C: 2SLS Estimates										
(a) Enrolls in TE - Men	1,954***	0.030***	2,679**	0.030*	−518.4	0.008	−2,472	−0.006	4,133***	0.054***
	(533.2)	(0.01)	(1,114)	(0.02)	(1,256)	(0.02)	(2,677)	(0.04)	(823.4)	(0.02)
(b) Enrolls in TE - Women	161.1	0.018	1,633	0.040	−1,639	0.030	1,885	−0.022	900.6	−0.003
	(599.7)	(0.01)	(1,072)	(0.02)	(1,206)	(0.02)	(2,156)	(0.04)	(905.8)	(0.03)
p-val: (a)=(b)	[0.0255]	[0.4789]	[0.4987]	[0.7324]	[0.5198]	[0.4583]	[0.2051]	[0.7938]	[0.0083]	[0.0701]
Complier mean in alternative - Men	23,517***	0.767***	27,073***	0.748***	29,940***	0.825***	29,119***	0.809***	16,129***	0.729***
	(462.9)	(0.01)	(965.0)	(0.01)	(1,132)	(0.02)	(2,329)	(0.03)	(691.5)	(0.01)
Complier mean in alternative - Women	18,655***	0.769***	17,769***	0.711***	24,388***	0.797***	20,049***	0.812***	14,816***	0.768***
	(505.5)	(0.01)	(897.2)	(0.02)	(1,084)	(0.02)	(1,783)	(0.04)	(786.0)	(0.02)
N Clusters - Men	37,238	37,238	8,122	8,122	8,156	8,156	3,636	3,636	15,913	15,913
N Clusters - Women	19,886	19,886	5,356	5,356	6,532	6,532	4,142	4,142	8,473	8,473
BW - Men	47.45	47.45	48.60	48.60	39.25	39.25	41.55	41.55	41.00	41.00
BW - Women	27.45	27.45	44.90	44.90	55.95	55.95	40.74	40.74	25.05	25.05

Notes: Panel A reports first-stage coefficients. Panel B reports reduced-form effects of assignment to TE. Panel C reports 2SLS estimates of the effects for (a) men and (b) women of enrolling in TE, corresponding to the β_g parameters in equation (3). Odd columns show effects on average annual earnings during the 2018–2019 period and even columns show effects on the probability of having positive earnings for at least one month in the same period. Columns 1–2 use the full sample of applicants in a margin of admission involving TE and a different field. The remaining columns focus on subsamples of applicants with science (22%), business (24%), health (11%), and other fields (43%) as the alternative to TE. Observations are weighted using a triangular kernel, with bandwidths optimally selected following Calonico et al. (2019). We also report p-values for the null hypothesis that β_g is the same for men and women, the estimated mean outcome for compliers assigned to the non-TE program, the number of clusters, and bandwidths by gender. Standard errors are clustered at the individual level and shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Effects of Enrollment in TE on Employment Outcomes in 2018-2019

	N of months employed in a year (1)	Permanent Contract (2)	Fixed-term Contract (3)	N of months of experience (4)	N of employers (5)
(a) Enrolls in TE - Men	0.388^{***}	0.055^{***}	-0.015^{*}	4.496^{***}	0.505^{***}
	(0.11)	(0.01)	(0.01)	(0.95)	(0.14)
(b) Enrolls in TE - Women	0.140	0.040^{***}	-0.009	2.514^{*}	0.444^{**}
	(0.17)	(0.02)	(0.01)	(1.45)	(0.20)
p-val: (a)=(b)	[0.2146]	[0.4086]	[0.7328]	[0.2526]	[0.8012]
Complier mean in alternative - Men	7.593^{***}	0.571^{***}	0.249^{***}	70.52^{***}	10.36^{***}
	(0.09)	(0.01)	(0.01)	(0.85)	(0.12)
Complier mean in alternative - Women	7.750^{***}	0.558^{***}	0.268^{***}	68.70^{***}	9.808^{***}
	(0.14)	(0.01)	(0.01)	(1.27)	(0.17)
N Clusters - Men	37,238	37,238	37,238	37,238	37,238
N Clusters - Women	19,886	19,886	19,886	19,886	19,886
BW - Men	47.45	47.45	47.45	47.45	47.45
BW - Women	27.45	27.45	27.45	27.45	27.45

Notes: This table reports 2SLS estimates of the effects of enrolling in TE on employment outcomes for (a) men and (b) women, corresponding to the β_g parameters in equation (3). Estimates are obtained using the full sample of applicants in an admission margin involving TE and a different field. Observations are weighted using a triangular kernel, with gender-specific optimal bandwidths. We also report p-values for tests of equality of the TE effect between men and women, the estimated mean of each outcome for compliers assigned to a non-TE program, and the number of clusters. Standard errors are clustered at the individual level and reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Effects of Enrollment in Business and Health on Earnings and Employment in 2018-2019

	Alternative Field									
	All non-Business 100%		TE 50%		Science & Math 1%		Health 7%		Other non-Business 42%	
	earnings	employment	earnings	employment	earnings	employment	earnings	employment	earnings	employment
Panel A: Business	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(a) Enrolls in Business - Men	1,289	0.009	542.9	−0.008	−2,756	−0.003	10,695	−0.158	3,372*	0.047
	(1,047)	(0.02)	(1,315)	(0.02)	(6,073)	(0.06)	(15,847)	(0.14)	(1,912)	(0.03)
(b) Enrolls in Business - Women	4,041***	−0.007	1,564	−0.029	5,361	0.057	11,105	0.109	4,486***	−0.021
	(1,065)	(0.02)	(1,150)	(0.02)	(3,807)	(0.06)	(9,893)	(0.16)	(1,273)	(0.03)
p-val: (a)=(b)	[0.0654]	[0.5330]	[0.5588]	[0.4903]	[0.2576]	[0.4827]	[0.9825]	[0.2156]	[0.6279]	[0.1139]
Complier mean in alternative - Men	27,232***	0.789***	27,945***	0.833***	50,691***	0.842***	31,639***	1.108***	22,049***	0.701***
	(878.3)	(0.01)	(1,097)	(0.02)	(5,554)	(0.06)	(10,792)	(0.15)	(1,599)	(0.03)
Complier mean in alternative - Women	19,618***	0.797***	21,950***	0.840***	29,953***	0.850***	21,645***	0.762***	16,997***	0.775***
	(829.5)	(0.02)	(951.9)	(0.02)	(3,519)	(0.05)	(6,093)	(0.15)	(975.0)	(0.02)
First stage - Men	0.475***	0.475***	0.485***	0.485***	0.592***	0.592***	0.602***	0.602***	0.449***	0.449***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.10)	(0.10)	(0.01)	(0.01)
First stage - Women	0.515***	0.515***	0.464***	0.464***	0.547***	0.547***	0.515***	0.515***	0.489***	0.489***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.08)	(0.08)	(0.01)	(0.01)
N Clusters - Men	14,206	14,206	8,156	8,156	672	672	92	92	5,438	5,438
N Clusters - Women	7,712	7,712	6,532	6,532	857	857	454	454	5,701	5,701
BW - Men	37.60	37.60	39.25	39.25	25.10	25.10	32.50	32.50	34.40	34.40
BW - Women	16.55	16.55	55.95	55.95	24.55	24.55	30.80	30.80	23.65	23.65

	Alternative Field									
	All non-Health 100%		TE 26%		Science & Math 34%		Business 3%		Other non-Health 37%	
	earnings	employment	earnings	employment	earnings	employment	earnings	employment	earnings	employment
Panel B: Health	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(a) Enrolls in Health - Men	3,011**	0.031	2,473	0.006	6,047***	0.090**	−10,964	0.162	1,334	−0.021
	(1,289)	(0.02)	(2,683)	(0.04)	(2,285)	(0.04)	(15,456)	(0.14)	(2,345)	(0.05)
(b) Enrolls in Health - Women	1,732	0.041*	−1,774	0.020	3,727**	0.025	−12,495	−0.123	3,775***	0.071**
	(1,071)	(0.02)	(2,031)	(0.04)	(1,520)	(0.03)	(11,108)	(0.19)	(1,331)	(0.03)
p-val: (a)=(b)	[0.4452]	[0.7748]	[0.2069]	[0.8041]	[0.3979]	[0.1741]	[0.9359]	[0.2243]	[0.3653]	[0.1007]
Complier mean in alternative - Men	23,317***	0.746***	26,404***	0.789***	22,074***	0.696***	37,552**	0.748***	20,809***	0.766***
	(1,066)	(0.02)	(2,180)	(0.03)	(1,897)	(0.03)	(16,710)	(0.13)	(2,068)	(0.04)
Complier mean in alternative - Women	18,664***	0.735***	22,857***	0.764***	19,556***	0.734***	27,408***	0.880***	14,816***	0.714***
	(869.8)	(0.02)	(1,636)	(0.03)	(1,300)	(0.03)	(10,389)	(0.16)	(1,110)	(0.03)
First stage - Men	0.533***	0.533***	0.560***	0.560***	0.583***	0.583***	0.588***	0.588***	0.467***	0.467***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.10)	(0.10)	(0.02)	(0.02)
First stage - Women	0.479***	0.479***	0.510***	0.510***	0.495***	0.495***	0.458***	0.458***	0.442***	0.442***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.08)	(0.08)	(0.01)	(0.01)
N Clusters - Men	11,765	11,765	3,636	3,636	3,342	3,342	92	92	4,007	4,007
N Clusters - Women	12,566	12,566	4,142	4,142	6,294	6,294	454	454	8,047	8,047
BW - Men	45.31	45.31	41.55	41.55	37.44	37.44	32.50	32.50	45.95	45.95
BW - Women	23.00	23.00	40.74	40.74	42.95	42.95	30.80	30.80	35.28	35.28

Notes: Panel A (Panel B) shows 2SLS estimates of the effects for (a) men and (b) women of enrolling in business (health). Odd columns show effects on average annual earnings during the 2018–2019 period and even columns show effects on the probability of having positive earnings for at least one month. Columns 1–2 use the full sample of applicants in a margin of admission involving business (health) and a different field. The remaining columns focus on the subsamples of applicants with other specified fields as the alternative to business (health). Estimates are obtained using local linear regressions with a triangular kernel and optimal bandwidths following Calonico et al. (2019), and observations are weighted using the corresponding optimal kernel weights. We also report: the p-values for the null hypothesis that effects are the same for men and women, the estimated mean of the outcome for compliers who enrolled in the non-business (non-health) cutoff program, the first-stage coefficients, and the number of clusters. Standard errors are clustered at the individual level and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effects of Enrollment in Science and STEM on Earnings and Employment in 2018-2019

	Alternative Field									
	All non-Science 100%		TE 36%		Business 6%		Health 25%		Other non-Science 33%	
	earnings	employment	earnings	employment	earnings	employment	earnings	employment	earnings	employment
Panel A: Science & Math	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(a) Enrolls in Science & Math - Men	$-2,463^{***}$	-0.041^{***}	$-2,829^{**}$	-0.031^{*}	3,097	0.003	$-6,462^{***}$	-0.096^{**}	49.54	-0.015
	(901.0)	(0.01)	(1,174)	(0.02)	(6,827)	(0.07)	(2,426)	(0.04)	(1,885)	(0.03)
(b) Enrolls in Science & Math - Women	$-2,110^{***}$	-0.005	$-1,681$	-0.041	$-6,169$	-0.066	$-3,595^{**}$	-0.024	-575.1	0.028
	(756.8)	(0.02)	(1,101)	(0.03)	(4,388)	(0.07)	(1,460)	(0.03)	(1,258)	(0.03)
p-val: (a)=(b)	[0.7642]	[0.0983]	[0.4757]	[0.7537]	[0.2537]	[0.4799]	[0.3113]	[0.1417]	[0.7828]	[0.3473]
Complier mean in alternative - Men	$27,280^{***}$	0.782^{***}	$29,315^{***}$	0.782^{***}	$38,116^{***}$	0.796^{***}	$29,898^{***}$	0.820^{***}	$19,789^{***}$	0.744^{***}
	(724.2)	(0.01)	(944.5)	(0.01)	(5,314)	(0.05)	(2,027)	(0.03)	(1,601)	(0.03)
Complier mean in alternative - Women	$18,849^{***}$	0.726^{***}	$18,705^{***}$	0.742^{***}	$33,415^{***}$	0.863^{***}	$22,369^{***}$	0.733^{***}	$14,348^{***}$	0.689^{***}
	(639.7)	(0.01)	(908.3)	(0.02)	(3,635)	(0.06)	(1,254)	(0.02)	(1,097)	(0.03)
First stage - Men	0.554^{***}	0.554^{***}	0.591^{***}	0.591^{***}	0.526^{***}	0.526^{***}	0.546^{***}	0.546^{***}	0.472^{***}	0.472^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
First stage - Women	0.508^{***}	0.508^{***}	0.544^{***}	0.544^{***}	0.475^{***}	0.475^{***}	0.513^{***}	0.513^{***}	0.455^{***}	0.455^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
N Clusters - Men	14,961	14,961	8,122	8,122	672	672	3,342	3,342	4,287	4,287
N Clusters - Women	13,842	13,842	5,356	5,356	857	857	6,294	6,294	5,940	5,940
BW - Men	36.96	36.96	48.60	48.60	25.10	25.10	37.44	37.44	32.20	32.20
BW - Women	25.50	25.50	44.90	44.90	24.55	24.55	42.95	42.95	26.80	26.80

	Alternative Field							
	All non-STEM 100%		Business 24%		Health 22%		Other non-STEM 54%	
	earnings	employment	earnings	employment	earnings	employment	earnings	employment
Panel B: STEM	(1)	(2)	(5)	(6)	(7)	(8)	(9)	(10)
(a) Enrolls in STEM - Men	327.5	0.011	-306.0	0.002	$-4,219^{**}$	-0.050^{*}	$2,865^{***}$	0.038^{**}
	(610.6)	(0.01)	(1,270)	(0.02)	(1,686)	(0.03)	(868.2)	(0.02)
(b) Enrolls in STEM - Women	$-1,284^{**}$	-0.001	$-2,684^{**}$	0.002	$-1,939^{*}$	-0.029	67.39	0.005
	(569.5)	(0.01)	(1,250)	(0.02)	(1,127)	(0.02)	(698.4)	(0.02)
p-val: (a)=(b)	[0.0536]	[0.4919]	[0.1822]	[0.9964]	[0.2610]	[0.5463]	[0.0121]	[0.1936]
Complier mean in alternative - Men	$23,394^{***}$	0.774^{***}	$30,621^{***}$	0.825^{***}	$29,012^{***}$	0.809^{***}	$17,271^{***}$	0.726^{***}
	(530.7)	(0.01)	(1,149)	(0.02)	(1,446)	(0.02)	(725.9)	(0.01)
Complier mean in alternative - Women	$19,145^{***}$	0.765^{***}	$25,928^{***}$	0.815^{***}	$21,582^{***}$	0.762^{***}	$14,737^{***}$	0.738^{***}
	(489.8)	(0.01)	(1,100)	(0.02)	(959.3)	(0.02)	(606.8)	(0.02)
First stage - Men	0.504^{***}	0.504^{***}	0.503^{***}	0.503^{***}	0.545^{***}	0.545^{***}	0.489^{***}	0.489^{***}
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
First stage - Women	0.467^{***}	0.467^{***}	0.464^{***}	0.464^{***}	0.501^{***}	0.501^{***}	0.439^{***}	0.439^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N Clusters - Men	32,658	32,658	8,846	8,846	7,178	7,178	15,077	15,077
N Clusters - Women	26,476	26,476	6,426	6,426	11,367	11,367	15,900	15,900
BW - Men	33.85	33.85	38.22	38.22	40.42	40.42	25.50	25.50
BW - Women	25.85	25.85	37.75	37.75	47.30	47.30	28.56	28.56

Notes: Panel A (Panel B) shows 2SLS estimates of the effects for (a) men and (b) women of enrolling in science (STEM). Odd columns show effects on average annual earnings during the 2018-2019 period and even columns show effects on the probability of having positive earnings for at least one month. Columns 1-2 use the full sample of applicants in a margin of admission involving science (STEM) and a different field. The remaining columns focus on the subsamples of applicants with other specified fields as the alternative to science (STEM). Observations are weighted using a triangular kernel with bandwidth $h = 30$ and standard errors are clustered at the individual level. We also report: the p-values for the null hypothesis that effects are the same for men and women, the estimated mean of the outcome for compliers who enrolled in the non-science (non-STEM) cutoff program, the first-stage coefficients, and the number of clusters. Standard errors are clustered at the individual level and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effects of Enrollment in TE on College Graduation

	Graduates:					
	College graduation	On-time college graduation	Years enrolled	Graduation from TE	Graduation from cutoff program	Years Enrolled in TE
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Enrolls in TE - Men	0.00	-0.05^{***}	0.18^{**}	0.36^{***}	0.28^{***}	3.11^{***}
	(0.01)	(0.01)	(0.07)	(0.01)	(0.01)	(0.08)
(b) Enrolls in TE - Women	-0.00	-0.07^{***}	0.08	0.38^{***}	0.33^{***}	3.00^{***}
	(0.02)	(0.02)	(0.11)	(0.02)	(0.01)	(0.11)
p-val: (a)=(b)	[0.812]	[0.265]	[0.430]	[0.380]	[0.001]	[0.431]
Complier mean in alternative - Men	0.70^{***}	0.31^{***}	5.80^{***}	0.18^{***}	0.04^{***}	1.47^{***}
	0.01	0.01	0.06	0.01	0.00	0.07
Complier mean in alternative - Women	0.77^{***}	0.41^{***}	5.81^{***}	0.11^{***}	0.02^{***}	0.83^{***}
	0.02	0.02	0.09	0.01	0.00	0.08
N Clusters - Men	20,101	20,101	20,101	20,101	20,101	20,101
N Clusters - Women	11,120	11,120	11,120	11,120	11,120	11,120

Notes: This table reports 2SLS estimates of the effects of enrolling in the TE cutoff program on several college graduation outcomes for (a) men and (b) women, corresponding to the β_g parameters in equation (3). Estimates are obtained using the full sample of applicants in a margin of admission involving TE and a different field. Because graduation outcomes are only available as of 2007, the analysis considers cohorts who graduated from high school between 2003 and 2007, and who should not have completed a university degree prior to 2007. Observations are weighted using a triangular kernel, with bandwidths optimally selected following Calonico et al. (2019). We also report the p-values for the null hypothesis that β_g is the same for men and women, the estimated mean outcome for compliers assigned to the non-TE program, and the number of clusters by gender. Standard errors are clustered at the individual level and shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Effects of Enrollment in TE on Sector and Firm of Employment

	Enrolls in TE		p-val	Complier mean in fallback		N Clusters	
	(a) Men	(b) Women	(a)=(b)	Men	Women	Men	Women
Firm sector:							
Agriculture	-0.012^{***}	-0.003	[0.0800]	0.032^{***}	0.024^{***}	37,238	19,886
	(0.00)	(0.00)		(0.00)	(0.00)		
Manufacturing	0.011^{**}	0.034^{***}	[0.0076]	0.059^{***}	0.035^{***}	37,238	19,886
	(0.01)	(0.01)		(0.00)	(0.01)		
Construction	0.037^{***}	0.017^{***}	[0.0117]	0.058^{***}	0.035^{***}	37,238	19,886
	(0.01)	(0.01)		(0.00)	(0.00)		
Mining and quarrying; Electricity, gas and water supply	0.018^{***}	0.012^{***}	[0.3597]	0.030^{***}	0.017^{***}	37,238	19,886
	(0.00)	(0.00)		(0.00)	(0.00)		
Information and Communication	0.016^{***}	0.014^{***}	[0.8480]	0.034^{***}	0.024^{***}	37,238	19,886
	(0.00)	(0.01)		(0.00)	(0.00)		
Commerce	0.000	-0.002	[0.8212]	0.097^{***}	0.086^{***}	37,238	19,886
	(0.01)	(0.01)		(0.01)	(0.01)		
Financial Activities	-0.003	-0.012	[0.3365]	0.071^{***}	0.070^{***}	37,238	19,886
	(0.01)	(0.01)		(0.00)	(0.01)		
Profesional and Scientific Activities	0.016^{***}	0.026^{***}	[0.2773]	0.065^{***}	0.051^{***}	37,238	19,886
	(0.01)	(0.01)		(0.00)	(0.01)		
Administrative Service Activities	0.008^{*}	0.010	[0.8373]	0.048^{***}	0.046^{***}	37,238	19,886
	(0.00)	(0.01)		(0.00)	(0.01)		
Public Administration and Defense	-0.044^{***}	-0.048^{***}	[0.7192]	0.118^{***}	0.161^{***}	37,238	19,886
	(0.01)	(0.01)		(0.01)	(0.01)		
Education	-0.024^{***}	-0.029^{***}	[0.6760]	0.074^{***}	0.116^{***}	37,238	19,886
	(0.00)	(0.01)		(0.00)	(0.01)		
Other Services	0.006	-0.001	[0.5383]	0.081^{***}	0.103^{***}	37,238	19,886
	(0.01)	(0.01)		(0.01)	(0.01)		
Sector characteristics:							
$> 1/3$ of female employees sector	-0.021^{**}	-0.005	[0.3781]	0.649^{***}	0.683^{***}	37,238	19,886
	(0.01)	(0.02)		(0.01)	(0.01)		
$< 1/3$ of female employees sector	0.049^{***}	0.027^{***}	[0.0176]	0.079^{***}	0.046^{***}	37,238	19,886
	(0.01)	(0.01)		(0.01)	(0.01)		
$> 2/3$ of female employees sector	-0.027^{***}	-0.026^{**}	[0.9250]	0.084^{***}	0.130^{***}	37,238	19,886
	(0.01)	(0.01)		(0.00)	(0.01)		
$< 2/3$ of female employees sector	0.054^{***}	0.048^{***}	[0.7185]	0.644^{***}	0.599^{***}	37,238	19,886
	(0.01)	(0.02)		(0.01)	(0.01)		
% of female employees (if employed) sector	-0.036^{***}	-0.037^{***}	[0.8540]	0.481^{***}	0.528^{***}	28,470	14,789
	(0.00)	(0.01)		(0.00)	(0.00)		
Sector average earnings	$1{,}059^{***}$	700.0^{**}	[0.3701]	$15{,}070^{***}$	$14{,}619^{***}$	37,202	19,867
	(225.6)	(331.5)		(187.6)	(274.9)		
Firm characteristics:							
Same region	0.015	0.025	[0.5937]	0.399^{***}	0.408^{***}	33,491	16,802
	(0.01)	(0.02)		(0.01)	(0.01)		
Different region	0.033^{***}	0.016	[0.3207]	0.287^{***}	0.269^{***}	33,491	16,802
	(0.01)	(0.01)		(0.01)	(0.01)		
Same province	0.022^{**}	0.019	[0.8857]	0.311^{***}	0.328^{***}	33,491	16,802
	(0.01)	(0.02)		(0.01)	(0.01)		
Different province	0.026^{**}	0.022	[0.8161]	0.375^{***}	0.349^{***}	33,491	16,802
	(0.01)	(0.02)		(0.01)	(0.01)		
$> 1/3$ of female employees	-0.076^{***}	-0.055^{***}	[0.2638]	0.434^{***}	0.600^{***}	37,238	19,886
	(0.01)	(0.02)		(0.01)	(0.01)		
$< 1/3$ of female employees	0.107^{***}	0.072^{***}	[0.0201]	0.286^{***}	0.128^{***}	37,238	19,886
	(0.01)	(0.01)		(0.01)	(0.01)		
$> 2/3$ of female employees	-0.013^{***}	-0.019	[0.6766]	0.059^{***}	0.153^{***}	37,238	19,886
	(0.00)	(0.01)		(0.00)	(0.01)		
$< 2/3$ of female employees	0.044^{***}	0.037^{**}	[0.6871]	0.662^{***}	0.575^{***}	37,238	19,886
	(0.01)	(0.02)		(0.01)	(0.01)		
% of female employees (if employed)	-0.057^{***}	-0.051^{***}	[0.5575]	0.397^{***}	0.535^{***}	26,814	13,864
	(0.01)	(0.01)		(0.00)	(0.01)		
$> 20\%$ of female leaders	-0.064^{***}	-0.051^{***}	[0.5088]	0.447^{***}	0.622^{***}	37,238	19,886
	(0.01)	(0.02)		(0.01)	(0.01)		
$< 20\%$ of female leaders	0.095^{***}	0.069^{***}	[0.0733]	0.274^{***}	0.105^{***}	37,238	19,886
	(0.01)	(0.01)		(0.01)	(0.01)		
% of female leaders (if employed)	-0.041^{***}	-0.033^{***}	[0.4477]	0.294^{***}	0.427^{***}	26,814	13,864
	(0.01)	(0.01)		(0.00)	(0.01)		
Firm average earnings	$1{,}143^{***}$	601.2	[0.2761]	$15{,}602^{***}$	$14{,}728^{***}$	37,226	19,881
	(290.2)	(403.5)		(241.7)	(336.8)		

Notes: This table reports 2SLS estimates of the effects of enrolling in the TE cutoff program on sector of employment and firm characteristics for (a) men and (b) women, corresponding to the β_g parameters in equation (3). Estimates are obtained using the full sample of applicants in a margin of admission involving TE and a different field. Observations are weighted using a triangular kernel, with bandwidths optimally selected following Calonico et al. (2019). We also report the p-values for the null hypothesis that β_g is the same for men and women, the estimated mean outcome for compliers assigned to the non-TE program, and the number of clusters by gender. Standard errors are clustered at the individual level and shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Effects of Enrollment in TE on Partner's Characteristics and Outcomes

	Has a child	Married	Has a partner (married or parent of child)	Has a Partner we can find in our sample	Partner perc. math score	Partner perc. lang. score	Partner enrolls same TE program	Partner enrolls other TE program	Partner annual earnings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(a) Enrolls in TE - Men	-0.01	-0.02^{**}	-0.01	-0.00	-1.16	-2.22^{**}	-0.03^{***}	0.03^{***}	-4
	(0.01)	(0.01)	(0.01)	(0.01)	(1.13)	(1.12)	(0.01)	(0.01)	(673)
(b) Enrolls in TE - Women	-0.02	0.00	-0.00	-0.02	4.77^{**}	6.23^{***}	-0.01	0.11^{***}	2,527
	(0.02)	(0.01)	(0.02)	(0.02)	(2.02)	(1.97)	(0.02)	(0.03)	(1,733)
p-val: (a)=(b)	[0.608]	[0.203]	[0.758]	[0.413]	[0.010]	[0.000]	[0.126]	[0.004]	[0.173]
Complier mean in alternative - Men	0.42^{***}	0.26^{***}	0.46^{***}	0.37^{***}	55.23^{***}	56.75^{***}	0.08^{***}	0.06^{***}	$13,126^{***}$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.99)	(0.99)	(0.01)	(0.01)	(583)
Complier mean in alternative - Women	0.48^{***}	0.25^{***}	0.50^{***}	0.33^{***}	57.43^{***}	50.90^{***}	0.11^{***}	0.16^{***}	$21,916^{***}$
	(0.01)	(0.01)	(0.01)	(0.01)	(1.71)	(1.68)	(0.01)	(0.02)	(1,406)
N Clusters - Men	37,388	37,388	37,388	37,388	12,929	12,929	12,929	12,929	12,929
N Clusters - Women	20,062	20,062	20,062	20,062	5,484	5,484	5,484	5,484	5,484

Notes: This table reports 2SLS estimates of the effects of enrolling in TE on partners' characteristics and outcomes for (a) men and (b) women, corresponding to the β_g parameters in equation (3). Considered outcomes include: the probability of having a child, being married, having a partner (we define two individuals as partners if they married or if they have a child registered with both of them as parents), having a partner for whom information is available, partner's math and language test score percentiles, the probability of having a partner who enrolled in the same TE program or in another TE program, and partner's annual earnings in 2016–2017. Estimates are obtained using the full sample of applicants in a margin of admission involving TE and a different field. Observations are weighted using a triangular kernel, with bandwidths optimally selected following Calonico et al. (2019). We also report the p-values for the null hypothesis that β_g is the same for men and women, the estimated mean outcome for compliers assigned to the non-TE program, the number of clusters, and bandwidths by gender. Standard errors are clustered at the individual level and shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Survey: Preferences and Job Characteristics

	Men						Women						Differences	
	All (1)	TE (2)	Science (3)	Business (4)	Health (5)	Other (6)	All (7)	TE (8)	Science (9)	Business (10)	Health (11)	Other (12)	M-W TE (13)	W TE - W Non-TE (14)
Employment status														
Dependent	0.79	0.84	0.73	0.76	0.79	0.76	0.78	0.81	0.70	0.79	0.86	0.75	0.027	0.034
													(0.031)	(0.027)
Self-employed	0.13	0.10	0.12	0.10	0.16	0.18	0.13	0.07	0.18	0.09	0.10	0.16	0.029	-0.070***
													(0.021)	(0.018)
Does not work	0.08	0.07	0.15	0.14	0.04	0.06	0.09	0.12	0.12	0.11	0.04	0.09	-0.057**	0.037
													(0.024)	(0.022)
Observations	1,526	491	96	259	141	528	2,289	234	125	301	368	1,238		
Preferences when looking for a job (% Strongly Agree)														
Flexible location and schedule	0.48	0.49	0.48	0.49	0.50	0.47	0.52	0.55	0.45	0.57	0.49	0.51	-0.054	0.033
													(0.040)	(0.034)
Fixed salary	0.40	0.34	0.48	0.29	0.51	0.47	0.55	0.49	0.55	0.45	0.60	0.57	-0.143***	-0.071**
													(0.039)	(0.034)
Work-life balance	0.77	0.78	0.70	0.76	0.85	0.75	0.86	0.81	0.86	0.83	0.90	0.86	-0.030	-0.055**
													(0.032)	(0.027)
Help others or useful to society	0.57	0.49	0.49	0.56	0.62	0.64	0.72	0.64	0.59	0.62	0.76	0.75	-0.152***	-0.085***
													(0.039)	(0.033)
Make a lot of money	0.19	0.21	0.14	0.17	0.20	0.20	0.16	0.17	0.11	0.16	0.18	0.16	0.041	0.014
													(0.031)	(0.026)
Job with interpersonal contact	0.31	0.27	0.17	0.35	0.32	0.34	0.45	0.35	0.28	0.40	0.53	0.47	-0.088**	-0.105***
													(0.037)	(0.033)
Job close to home	0.33	0.33	0.25	0.28	0.45	0.35	0.41	0.41	0.44	0.40	0.45	0.41	-0.080**	-0.004
													(0.039)	(0.034)
Career advancement opportunities	0.46	0.53	0.32	0.50	0.39	0.43	0.38	0.52	0.38	0.47	0.27	0.37	0.014	0.148***
													(0.040)	(0.034)
Same sex coworkers (% Agree or Strongly Agree)	0.04	0.03	0.02	0.05	0.06	0.04	0.20	0.22	0.29	0.24	0.13	0.20	-0.185***	0.020
													(0.028)	(0.028)
Observations	1,526	491	96	259	141	528	2,289	234	125	301	368	1,238		
Job characteristics (% Strongly Agree)														
Flexible location and schedule	0.34	0.41	0.40	0.38	0.20	0.29	0.28	0.30	0.39	0.36	0.16	0.28	0.104***	0.028
													(0.040)	(0.034)
Fixed salary	0.53	0.54	0.62	0.52	0.56	0.50	0.57	0.66	0.53	0.59	0.51	0.56	-0.115***	0.103***
													(0.041)	(0.035)
Work-life balance	0.33	0.34	0.30	0.44	0.33	0.28	0.29	0.31	0.35	0.33	0.25	0.28	0.031	0.026
													(0.039)	(0.034)
Help others or useful to society	0.43	0.34	0.40	0.42	0.67	0.46	0.56	0.39	0.46	0.42	0.73	0.58	-0.045	-0.193***
													(0.041)	(0.036)
Make a lot of money	0.12	0.12	0.13	0.14	0.21	0.07	0.07	0.08	0.05	0.09	0.12	0.05	0.044*	0.012
													(0.024)	(0.020)
Job with interpersonal contact	0.41	0.33	0.32	0.34	0.55	0.48	0.53	0.36	0.38	0.37	0.72	0.55	-0.027	-0.186***
													(0.040)	(0.035)
Job close to home	0.35	0.35	0.43	0.34	0.38	0.34	0.37	0.33	0.48	0.34	0.38	0.38	0.015	-0.046
													(0.040)	(0.035)
Career advancement opportunities	0.18	0.20	0.20	0.18	0.16	0.16	0.13	0.16	0.16	0.19	0.13	0.12	0.038	0.030
													(0.032)	(0.027)
Observations	1,405	458	82	222	135	497	2,082	205	110	267	352	1,126		
Female coworkers														
Less than 40% women coworkers	0.32	0.52	0.26	0.29	0.12	0.21	0.15	0.44	0.28	0.24	0.05	0.09	0.083**	0.323***
													(0.042)	(0.035)
Less than 40% women in senior positions	0.51	0.69	0.40	0.52	0.21	0.45	0.42	0.71	0.60	0.55	0.27	0.36	-0.024	0.325***
													(0.038)	(0.034)
Observations	1,526	491	96	259	141	528	2,289	234	125	301	368	1,238		

Notes: This table shows information on employment status, employment characteristics, preferences for different job attributes and actual job attributes for men and women who pursued a career in TE, science, business, health or other fields. The data comes from a survey that we designed and administered. The survey was sent by email by 12 of the 25 institutions participating in the centralized system of admission to former students who enrolled between 2000 and 2008.

Table 10: Survey: Career satisfaction, societal barriers, discrimination

	Men						Women						Differences	
	All (1)	TE (2)	Science (3)	Business (4)	Health (5)	Other (6)	All (7)	TE (8)	Science (9)	Business (10)	Health (11)	Other (12)	M-W TE (13)	W TE - W Non-TE (14)
Career Satisfaction (% Strongly Agree)														
Motivates and excites me														
% Strongly Agree	0.41	0.43	0.52	0.27	0.46	0.43	0.46	0.32	0.49	0.32	0.55	0.48	0.109***	-0.147***
													(0.038)	(0.033)
According to abilities														
% Strongly Agree	0.47	0.52	0.49	0.42	0.48	0.44	0.46	0.45	0.38	0.42	0.51	0.47	0.073*	-0.017
													(0.040)	(0.034)
Professional development														
% Strongly Agree	0.49	0.52	0.50	0.51	0.52	0.45	0.45	0.39	0.38	0.48	0.58	0.42	0.132***	-0.065*
													(0.039)	(0.034)
Job satisfaction														
Mean (1 to 10)	7.42	7.40	7.62	7.71	7.55	7.23	7.24	7.35	7.28	7.32	7.35	7.18	0.051	0.113
													(0.141)	(0.123)
Life Satisfaction														
Mean (1 to 10)	7.80	7.96	7.46	8.01	7.87	7.61	7.82	7.91	7.78	7.95	7.98	7.72	0.041	0.108
													(0.135)	(0.116)
Observations	1,526	491	96	259	141	528	2,289	234	125	301	368	1,238		
Societal Barriers (% Agree or Strongly Agree)														
Gender hurt job search	0.07	0.07	0.06	0.05	0.11	0.08	0.34	0.50	0.37	0.47	0.14	0.33	-0.437***	0.187***
													(0.035)	(0.034)
Family hindered career	0.18	0.16	0.20	0.15	0.26	0.20	0.42	0.49	0.36	0.35	0.40	0.44	-0.330***	0.071**
													(0.037)	(0.034)
Work hurt family life	0.43	0.45	0.39	0.36	0.50	0.44	0.55	0.53	0.52	0.51	0.57	0.56	-0.086**	-0.019
													(0.040)	(0.034)
Willing to sacrifice	0.51	0.53	0.51	0.60	0.39	0.48	0.40	0.51	0.36	0.52	0.29	0.39	0.015	0.123***
													(0.040)	(0.034)
Observations	1,526	491	96	259	141	528	2,289	234	125	301	368	1,238		
Felt discrimination sometimes, frequently or always in:														
Promotion at work	0.37	0.37	0.28	0.31	0.36	0.41	0.54	0.66	0.57	0.54	0.47	0.53	-0.292***	0.137***
													(0.038)	(0.033)
Decision making	0.48	0.43	0.44	0.44	0.48	0.55	0.66	0.72	0.70	0.61	0.59	0.67	-0.297***	0.073**
													(0.037)	(0.031)
Earnings	0.46	0.49	0.28	0.41	0.35	0.49	0.62	0.77	0.63	0.69	0.42	0.64	-0.279***	0.167***
													(0.036)	(0.029)
Job evaluations	0.33	0.32	0.29	0.24	0.30	0.39	0.41	0.45	0.50	0.37	0.35	0.41	-0.137***	0.052
													(0.039)	(0.034)
Development opportunities	0.38	0.40	0.29	0.35	0.37	0.41	0.50	0.58	0.48	0.52	0.48	0.48	-0.182***	0.091***
													(0.039)	(0.034)
Task assignment	0.41	0.38	0.36	0.34	0.44	0.46	0.57	0.60	0.63	0.58	0.48	0.58	-0.215***	0.031
													(0.039)	(0.034)
Observations	1,526	491	96	259	141	528	2,289	234	125	301	368	1,238		

Notes: This table shows responses on issues related to gender, career satisfaction, discrimination and career development for men and women who pursued a career in TE, science, business, health or other fields. The data comes from a survey that we designed and administered. The survey was sent by email by 14 of the 25 institutions participating in the centralized system of admission to former students who enrolled between 2000 and 2008.

Appendix - For Online Publication

February 28, 2026

A Sexism in Latin America and the U.S

Table A.1: Sexism in Latin America and the U.S.

	United States (1)	Chile (2)	Argentina (3)	Brasil (4)	Colombia (5)	Mexico (6)	Peru (7)
	% Agree or strongly agree						
When jobs are scarce, men should have more right to a job than women	5.7%	17.6%	15.0%	16.8%	22.4%	16.8%	17.6%
If a woman earns more money than her husband, it's almost certain to cause problems	12.4%	33.7%	20.0%	33.5%	43.8%	43.3%	25.1%
When a mother works for pay, the children suffer	24.9%	36.0%		60.4%	42.4%	43.6%	36.3%
On the whole, men make better political leaders than women do	19.4%	27.0%	27.0%	28.3%	27.4%	23.0%	18.9%
A university education is more important for a boy than for a girl	6.5%	20.1%	17.0%	9.3%	10.8%	20.7%	14.4%
On the whole, men make better business executives than women do	11.6%	18.3%	22.6%	28.7%	19.6%	20.4%	14.8%

Notes: This table uses data from the World Value Survey wave 6 (2010-2014) for the United States, Chile, Argentina, Brazil, Colombia, Mexico and Perú. It shows the percentage of individuals in each country who agree or strongly agree with each statement.

B Data Construction

Earnings records were obtained from the unemployment insurance records of Chile's Ministry of Labor for the period between 2002 and 2019. This data had to be accessed on-site at the Ministry of Labor. Because unemployment insurance records do not include public sector employees we added data from the public sector for the 2018-2019 period. Data on public sector employees was collected from https://www.portaltransparencia.cl and contains information for 596,517 and 639,797 employees in 2018 and 2019. These records exclude the police, military and armed forces.

To add educational records 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 2007 period. Although DEMRE has data on educational records for students who took the test as of 1999, we were unable to have both agencies work together to match the data. Instead, we turned to publicly available educational records stored in *El Mercurio* to gather information on students' unique national identification numbers (NIDs) and test score results. This data was then matched with earnings records, fertility records and other educational information at the Ministry of Labor. Of the total number of individuals who were in the margin of admission to TE and non-TE between 1999 and 2007, 97% were matched to national identification numbers and could be matched with earnings and fertility records. This is the sample we use in our study.

C Employment Status by Field and Gender in Chile

Table C.1 uses data from Casen 2017[1], a survey representative of the Chilean population, to categorize the percentage of individuals aged 29 to 38 years old who graduated from each field of study that are unemployed, employed in the private sector, public sector, or self-employed. Our earnings records prevent us from seeing the self-employed which represent roughly 10% of individuals.

Table C.1: Employment by Field of Graduation

			Employment			
		Obs	Unemployed	Employed Private Sector	Employed Public Sector	Self Employed
			(1)	(2)	(3)	(4)
Field						
TE	Male	579	0.088	0.692	0.126	0.093
	Female	203	0.137	0.673	0.102	0.089
Science	Male	25	0.063	0.863	0.058	0.015
	Female	30	0.183	0.585	0.120	0.112
Business & Adm	Male	232	0.080	0.631	0.170	0.118
	Female	242	0.170	0.642	0.103	0.085
Health	Male	148	0.151	0.239	0.503	0.107
	Female	298	0.120	0.279	0.554	0.047
Others	Male	645	0.113	0.505	0.231	0.152
	Female	1,123	0.139	0.467	0.317	0.077

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

[1] Ministerio de Desarrollo Social y Familia (2018)

D Sample Construction

For the purpose of our analysis, we constructed a sample of applicants who are on the margins of admission for programs in TE and non-TE, and whose assignment into one or the other depends on their weighted scores being above or below a predetermined cutoff. Our data show that 45% of students who apply to TE also submit applications for programs in other fields, while 55% exclusively apply within the TE domain. Table D.1 shows the socioeconomic characteristics and test scores of men and women who apply solely to TE or who apply to both TE and alternative fields. The table also shows the characteristics of men and women who have TE as a more or less preferred alternative.

In our analysis we further restrict our sample to include all programs that are oversubscribed. Also, to increase the strength of our first stage we eliminate applications that are not relevant for students' admissions. To illustrate this, consider an applicant i who applied to program j and whose weighted score for this program is s_{ij}. We need first to determine whether the admission cutoff for j, c_j is relevant for i's admission. As several papers have pointed out, it may not be (e.g., Abdulkadiroğlu et al., 2014). Suppose for instance that j is a very selective program, and that our applicant ranked it below a less selective program k. For this applicant, crossing j's admission cutoff does not affect assignment to j, because the less selective but preferred program k is within reach when $s_{ij} = c_j$. 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.

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

i) i ranks k above j, and

ii) k is *relatively less selective* than j from i's perspective, where relative selectivity is defined as follows:

Definition 1 *(Relative Selectivity)* *Let* $\phi_{il} = \frac{c_l - s_{il}}{\sqrt{\sum_{\forall\iota}(\alpha_l^\iota)^2}} = \frac{c_l - \sum_{\forall\iota} s_i^\iota \alpha_l^\iota}{\sqrt{\sum_{\forall\iota}(\alpha_l^\iota)^2}}$ *be the euclidean distance between i's vector of scores,* $(s_i^\iota)_{\forall\iota}$*, and the admission frontier for l defined as* $C_l =$

$\{(s^\iota)_{\forall\iota} : \sum_{\forall\iota} s^\iota \alpha_l = c_l\}$. *Then program k is said to be relatively more selective from i's perspective than program $j \neq k$ if and only if $\phi_{ik} > \phi_{ij}$.*[2]

Approximately 55% of the applications in our data survive the elimination process described by i) and ii).

[2]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 of admission cutoffs c_j and c_k. When this is not the case, our definition of relative selectivity takes into account the scores of the applicant. For a student with a high score in math and a low score in language, a program that gives a high weight to the math section will be relatively less selective than a program that gives more weight to the language section. In contrast, for a student that does better in language and worse in math, the opposite will be the case.

Table D.1: Characteristics of TE Applicants

	Men				Women			
	TE vs TE	TE vs Not TE	TE $\succ$ Non-TE	TE $\prec$ Non-TE	TE vs TE	TE vs Non-TE	TE $\succ$ Non-TE	TE $\prec$ Non-TE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Socioeconomic Characteristics								
Lives in the capital	0.37	0.37	0.39	0.35	0.38	0.32	0.34	0.32
	(0.48)	(0.48)	(0.49)	(0.48)	(0.48)	(0.47)	(0.47)	(0.46)
Total HH members	4.50	4.54	4.56	4.53	4.49	4.56	4.56	4.56
	(1.59)	(1.64)	(1.68)	(1.61)	(1.58)	(1.57)	(1.59)	(1.55)
Total HH members work	1.28	1.29	1.30	1.29	1.23	1.24	1.25	1.24
	(0.70)	(0.73)	(0.74)	(0.72)	(0.68)	(0.68)	(0.68)	(0.67)
Head of HH father	0.73	0.72	0.73	0.72	0.68	0.69	0.69	0.69
	(0.44)	(0.45)	(0.45)	(0.45)	(0.46)	(0.46)	(0.46)	(0.46)
Head of HH mother	0.21	0.22	0.22	0.22	0.25	0.24	0.24	0.24
	(0.41)	(0.41)	(0.41)	(0.41)	(0.44)	(0.43)	(0.43)	(0.43)
Mother primary ed	0.11	0.13	0.13	0.13	0.11	0.13	0.13	0.14
	(0.32)	(0.33)	(0.33)	(0.34)	(0.31)	(0.34)	(0.33)	(0.34)
Mother secondary ed	0.49	0.48	0.46	0.49	0.48	0.50	0.49	0.50
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Mother tertiary ed	0.40	0.40	0.42	0.38	0.40	0.37	0.39	0.36
	(0.49)	(0.49)	(0.49)	(0.48)	(0.49)	(0.48)	(0.49)	(0.48)
Father primary ed	0.11	0.12	0.12	0.12	0.11	0.13	0.13	0.14
	(0.31)	(0.32)	(0.32)	(0.33)	(0.31)	(0.34)	(0.34)	(0.34)
Father secondary ed	0.40	0.40	0.39	0.42	0.40	0.42	0.41	0.43
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)	(0.50)
Father tertiary ed	0.49	0.48	0.50	0.46	0.49	0.44	0.46	0.43
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Father works full-time	0.73	0.72	0.72	0.71	0.69	0.68	0.68	0.68
	(0.44)	(0.45)	(0.45)	(0.45)	(0.46)	(0.47)	(0.46)	(0.47)
Father works part-time	0.10	0.11	0.10	0.11	0.11	0.12	0.12	0.12
	(0.30)	(0.31)	(0.30)	(0.31)	(0.31)	(0.33)	(0.33)	(0.33)
Mother works full-time	0.38	0.38	0.39	0.37	0.39	0.37	0.37	0.36
	(0.48)	(0.49)	(0.49)	(0.48)	(0.49)	(0.48)	(0.48)	(0.48)
Mother works part-time	0.05	0.05	0.06	0.05	0.05	0.05	0.05	0.05
	(0.22)	(0.23)	(0.23)	(0.23)	(0.22)	(0.22)	(0.22)	(0.22)
Academic Performance								
GPA	5.90	5.88	5.91	5.86	6.08	6.03	6.05	6.02
	(0.45)	(0.48)	(0.49)	(0.47)	(0.43)	(0.44)	(0.45)	(0.44)
Language Score Percentile	68.31	69.67	70.81	68.78	68.12	66.37	67.64	65.60
	(21.25)	(21.76)	(22.03)	(21.51)	(20.68)	(21.41)	(21.66)	(21.23)
Math Score Percentile	80.82	77.03	78.65	75.79	77.58	70.77	72.34	69.82
	(16.63)	(19.05)	(19.13)	(18.89)	(17.41)	(19.90)	(20.29)	(19.61)
Obs	117,826	68,882	29,926	38,956	30,800	51,555	19,377	32,178

Notes: This table shows descriptive statistics for male and female applicants from 2000 to 2008 who: (i) applied solely to TE (columns 1 and 5), (ii) applied to both TE and alternative fields (columns 2 and 6), (iii) applied to TE and an alternative field, with TE as the more preferred option (columns 3 and 7), and (iv) applied to TE and an alternative field, with TE as the less preferred option (columns 4 and 8).

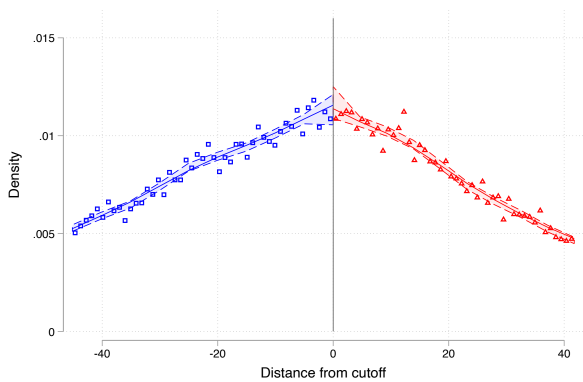
E Regression Discontinuity Validation

In this section we present standard tests of the validity of our RD strategy. We first check for manipulation of the running variable. 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. We do this by implementing the test suggested by Cattaneo et al. (2018), the results of which are presented in Figure E.1 for men and women in our sample. As expected, we do not detect discontinuities in the distribution of the running variable.

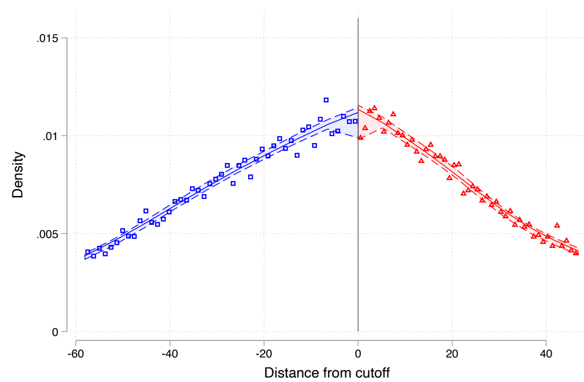
Next, we perform balancing checks to examine whether individuals just above and just below the cutoff are similar in terms of their baseline observable characteristics. We focus on a set of socioeconomic variables, including family size, parents' education, and parents' work status. Large and significant 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 identification assumptions.

Figure E.2 summarizes results for men and women in our sample. The figure plots the estimated discontinuities at the cutoff and their 95% confidence intervals. These coefficients are separately estimated for men and women from a specification analogous to (2), where the baseline characteristic is used as the dependent variable. An F-test for each sample rejects that these estimates are jointly significant.

Figure E.1: Running Variable Density Test



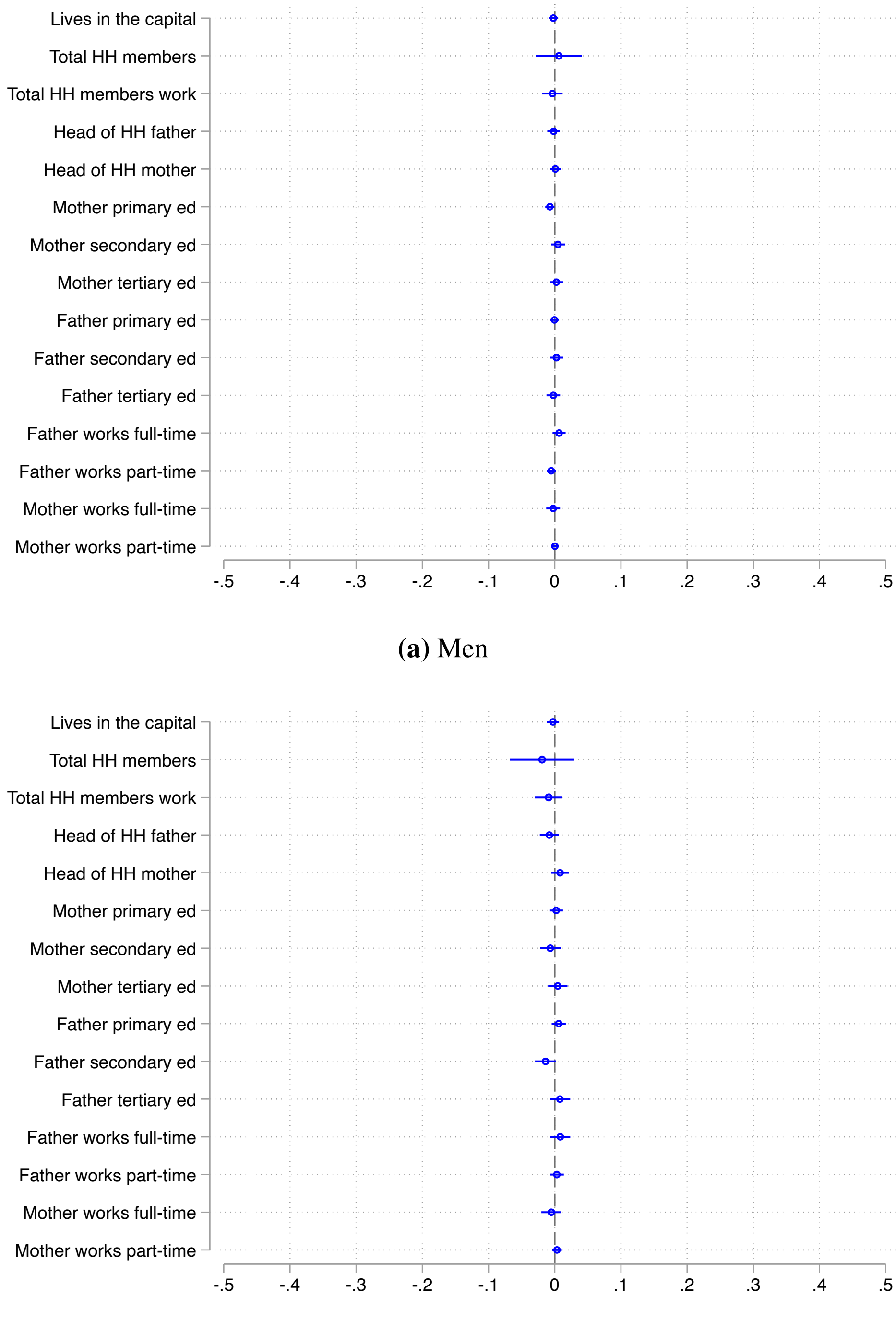
(a) Men



(b) Women

Notes: This figure illustrates the density of (a) men and (b) women's PSU scores around the cutoff. The density and its confidence intervals on each side of the cutoff were estimated following Cattaneo et al. (2018). This chart complements the formal test they suggest to study discontinuities in the distribution of the running variable around the relevant threshold. In this case, its p-value is 0.5317 for men and 0.9862 for women. This means there is no statistical evidence to reject the null hypothesis of a smooth density around the threshold.

Figure E.2: Continuity of Baseline Covariates



(b) Women

Notes: This figure illustrates the coefficients obtained when studying discontinuities in baseline covariates for (a) men and (b) women. Dots represent point estimates and blue lines show 95% confidence intervals. The F-test for joint significance for men has an F statistic of 1.04 $P > F = 0.4125$. The F-test for joint significance for women has an F statistic of 0.78 $P > F = 0.6869$.

F Robustness Checks

- Table F.1 reports robustness checks for our main estimates under alternative functional-form specifications (plus a version with additional controls). For Table F.1, we vary the functional form used to approximate the dependence of outcomes on the running variable in both the reduced-form equation (2) and the 2SLS specification in equation (3). For expositional simplicity, we suppress the gender and application-year subscripts and write the second stage as

  $$y_{ij} = \beta \cdot TE^e_{ij} + f_j(r_{ij}) + \xi_j + \varepsilon_{ij},$$

  where $f_j(r_{ij})$ collects the score terms. The reduced form and first stage use the analogous specification, replacing TE^e_{ij} with TE^a_{ij} as appropriate, and using the same choice of $f_j(\cdot)$ in both stages. Let $A_j = \mathbb{1}(j \in TE)$ indicate whether the target program is in TE, and let TE^a_j denote assignment to TE near the cutoff for applicants to program j. The specifications in Table F.1 differ only in the choice of $f_j(r)$:

  $$\text{Baseline (two slopes):} \quad f_j(r) = \delta_1 r + \delta_2 (TE^a_j \times r).$$

  $$\text{Flexible linear (four slopes):} \quad f_j(r) = \delta_1 r + \delta_2 (TE^a_j \times r) + \delta_3 (A_j \times r) + \delta_4 (A_j \times TE^a_j \times r).$$

  $$\text{Quadratic:} \quad f_j(r) = \delta_1 r + \delta_2 (TE^a_j \times r) + \kappa_1 r^2 + \kappa_2 (TE^a_j \times r^2).$$

  Specification (2) of Table F.1 additionally includes controls.

  Results are shown separately for imputed earnings (Panel A) and non-imputed earnings (Panel B). Earnings records from the unemployment insurance are capped at roughly $5,000 a month; to address this, we follow Card et al. (2013) and use Tobit models to stochastically impute the upper tail of the wage distribution. Across all specifications, the estimated returns to TE are very stable.

- Figure F.1 shows that results on annual earnings in 2018-2019 remain similar if we use alternative uniform bandwidths instead of optimal bandwidths.

- Table F.2 Panel A presents the impact of TE admission on the probability of being admitted into specific TE subfields for both men and women. These subfields include construction, industry and production, computing, engineering, and other related areas. Programs in the Cine-UNESCO TE category are classified into subfields using their OECD subclassification.

- Table F.3 reports the effects of assignment into TE on several outcomes. These include the probability of being accepted into the target program, the preference rank of the accepted program, the probability of being accepted into an elite institution, and the probability of being accepted into an institution outside the individual's hometown region. The table also presents the impact on the average earnings and peer characteristics of the programs to which individuals are accepted.

- Table F.4 re-estimates the earnings model using the same 2SLS specification, but re-weighting the data so that the distribution of women's applications looks the same as the distribution of men's applications, and vice versa. Specifically, when using the distribution of male applicants, we weight women's observations by n^m_{kj}/n^f_{jk}, and when using the distribution of female applicants, we weight men's observations by n^f_{jk}/n^m_{jk}, where n^g_{jk} is the number of gender g applicants applying to program j and whose next-best alternative is program k. We focus only on programs in the common support of male and female applications, that is, programs with applicants of both genders. Table F.2 Panels B and C confirm that after reweighting, men and women admitted into TE programs have the same probability of being admitted in TE subfields such as construction, industry and production, computing, engineering, or other areas.[3] Moreover, Table F.4 shows that the estimates on earnings using the weighted sample are similar to those from the unweighted analysis.

- Table F.5 documents how assignment to TE affects the characteristics of the assigned program differently depending on applicants' relative field preferences. For applicants who rank TE above the alternative (TE $\succ$ Alt), admission to TE entails enrollment in programs with substantially higher average earnings and higher-achieving peers in math, consistent with moving into a more preferred and more selective environment. For applicants who rank TE

[3]This is true by construction near the admission cutoff. Small gender differences in admission probabilities are due to students above the cutoff ending up assigned to a more preferred program in a field different from that of the target program, or students below the cutoff ending up assigned to a less preferred program in a field different from that of the fallback program.

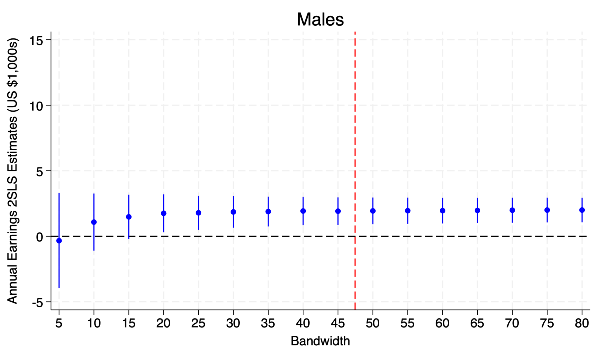
below the alternative (Alt $\succ$ TE), the effects run in the opposite direction, with admission to TE leading to programs with lower average earnings and weaker peer quality. These contrasting patterns highlight why pooling both types of applicants eliminates any mechanical link between TE enrollment and program selectivity or quality.

- Table F.6 examines heterogeneity in the earnings returns to enrolling in a TE program by applicants' relative field preferences. It reports 2SLS estimates separately for applicants who rank TE above the alternative program and those who rank the alternative above TE, for men and women. The table shows that while returns to TE are similar across preference groups for men, they differ for women: women who rank TE above the alternative experience negative earnings effects, whereas those who rank TE below the alternative experience positive effects. The difference between these two estimates is statistically significant for women, highlighting substantial heterogeneity in returns to TE by relative field preferences.

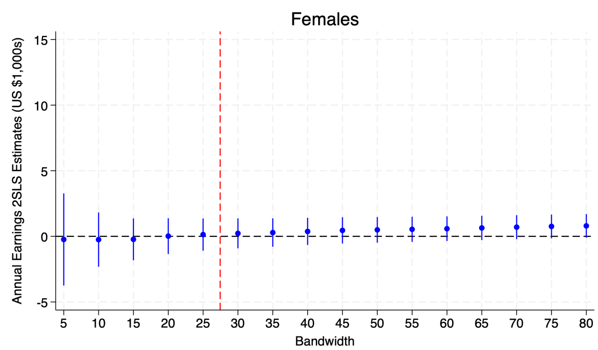
- Table F.7 shows results for the subsample of students choosing between TE and a different field within the same institution. The results remain consistent, even when focusing on this subsample, where institutional selectivity remains unchanged.

- Table F.8 shows that results on annual earnings in 2018-2019 remain similar if we re-estimate the earnings model using the same 2SLS specification but re-weight the data so that the distribution of women's math scores mirrors that of men's math scores, and vice versa. Specifically, we divide the applicants into 18 equally spaced groups based on their math test scores. When using the distribution of male applicants, we weight women's observations by n_s^m / n_s^f; conversely, when using the distribution of female applicants, we weight men's observations by n_s^f / n_s^m, where n_s^g is the number of applicants of gender g with scores s.

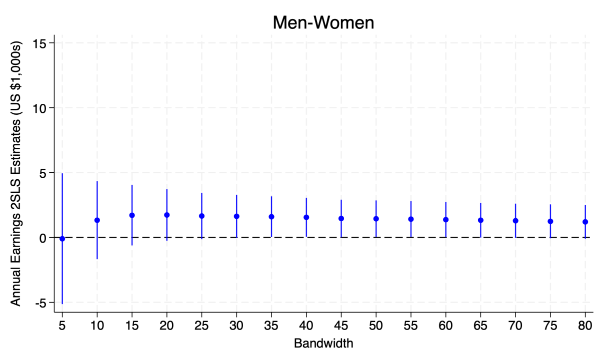
Figure F.1: Sensitivity of Estimates to Alternative Bandwidths



(a) Men



(b) Women



(c) Men-women

Notes: This figure shows 2SLS estimates of the effect of enrollment in a TE program on annual earnings in 2018–2019 using alternative bandwidths. Panel (a) reports estimates for men, panel (b) reports estimates for women, and panel (c) reports the difference between the estimated effects for men and women. Dots represent point estimates and vertical lines indicate 95% confidence intervals. Red dashed vertical lines in panels (a) and (b) indicate the optimal bandwidths selected following Calonico et al. (2019). In panel (c), estimates are computed using a common bandwidth for men and women; since optimal bandwidths are gender-specific, no optimal bandwidth is indicated.

Table F.1: Effects of enrollment in TE on Earnings and Employment - Alternative Specifications

N°	2-slopes	2-slopes + Controls	Quadratic	4-slopes	Alternative in different field		Alternative in Science & Math		Alternative in Business		Alternative in Health		Alternative in other fields	
					Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Panel A: Imputed Earnings														
(1)	✓				1,954***	161.1	2,679**	1,633	−518.4	−1,639	−2,472	1,885	4,133***	900.6
					(533.2)	(599.7)	(1,114)	(1,072)	(1,256)	(1,206)	(2,677)	(2,156)	(823.4)	(905.8)
(2)	✓	✓			1,934***	185.9	2,493**	1,693	−683.7	−1,517	−2,486	2,380	4,135***	932.6
					(533.0)	(600.3)	(1,115)	(1,072)	(1,247)	(1,202)	(2,647)	(2,175)	(823.4)	(907.3)
(3)	✓		✓		1,929***	147.1	2,463*	926.9	−1,520	−2,730*	−695.3	2,289	4,086***	639.8
					(655.5)	(784.1)	(1,381)	(1,313)	(1,543)	(1,420)	(2,868)	(2,214)	(1,012)	(1,233)
(4)	✓			✓	1,624*	−22.14	1,991	572.6	−2,667	−3,259*	273.0	3,241	3,779***	43.49
					(838.5)	(1,059)	(1,756)	(1,684)	(1,961)	(1,753)	(3,537)	(2,685)	(1,301)	(1,717)
Panel B: Non-imputed Earnings														
N°	2-slopes	2-slopes + Controls	Quadratic	4-slopes	Alternative in different field		Alternative in Science & Math		Alternative in Business		Alternative in Health		Alternative in other fields	
					Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
(1)	✓				1,132***	0.474	2,000**	1,598*	−361.6	−1,632*	−5,080**	635.7	3,146***	706.2
					(382.4)	(544.2)	(778.6)	(969.4)	(825.2)	(986.6)	(2,207)	(2,075)	(650.9)	(864.5)
(2)	✓	✓			1,126***	28.53	1,903**	1,655*	−456.0	−1,587	−5,142**	1,101	3,163***	721.9
					(382.4)	(545.3)	(794.9)	(963.5)	(824.0)	(988.8)	(2,172)	(2,093)	(652.3)	(864.8)
(3)	✓		✓		1,289***	96.35	1,730*	1,002	−854.6	−2,547**	−3,801	1,080	3,369***	547.4
					(474.4)	(701.5)	(906.1)	(1,158)	(1,016)	(1,155)	(2,417)	(2,157)	(825.1)	(1,168)
(4)	✓			✓	1,120*	−19.69	1,150	707.9	−1,635	−2,935**	−3,024	2,063	3,265***	32.86
					(608.8)	(936.3)	(1,097)	(1,474)	(1,298)	(1,420)	(2,927)	(2,663)	(1,076)	(1,600)

Notes: This table reports robustness checks for our main estimates under alternative empirical specifications. (1) shows the baseline specification. (2) and (3) augment the baseline specification by adding controls and allowing for quadratic polynomials in the running variable, respectively. (4) estimates a more flexible specification that allows slopes to vary both by assignment to TE and by whether TE is the target or fallback program. Panel A reports results using imputed earnings, while Panel B restricts the sample to non-imputed earnings. Standard errors are clustered at the individual level and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table F.2: Effect of TE Admission on Major of Admission - Reweighted Estimates by Application Margin

	Construction	Industry & Production	Computing	Engineering	Others
	(1)	(2)	(3)	(4)	(5)
Panel A: All					
(a) Admitted to TE - Men	0.09***	0.20***	0.14***	0.26***	0.07***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(b) Admitted to TE - Women	0.07***	0.30***	0.10***	0.23***	0.13***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
p-val: (a)=(b)	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Complier mean in alternative - Men	0.01	0.02	0.02	0.04	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Complier mean in alternative - Women	0.00	0.01	0.00	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N Clusters - Men	37,388	37,388	37,388	37,388	37,388
N Clusters - Women	20,062	20,062	20,062	20,062	20,062
Panel B: Using Male Distribution					
(a) Admitted to TE - Men	0.08***	0.18***	0.15***	0.22***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(b) Admitted to TE - Women	0.09***	0.21***	0.14***	0.25***	0.08***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
p-val: (a)=(b)	[0.013]	[0.013]	[0.401]	[0.001]	[0.000]
Complier mean in alternative - Men	0.01	0.02	0.02	0.04	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Complier mean in alternative - Women	0.00	0.01	0.00	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N Clusters - Men	28,494	28,494	28,494	28,494	28,494
N Clusters - Women	15,778	15,778	15,778	15,778	15,778
Panel C: Using Female Distribution					
(a) Admitted to TE - Men	0.06***	0.23***	0.10***	0.21***	0.09***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
(b) Admitted to TE - Women	0.07***	0.27***	0.10***	0.23***	0.11***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
p-val: (a)=(b)	[0.056]	[0.000]	[0.399]	[0.043]	[0.000]
Complier mean in alternative - Men	0.01	0.02	0.02	0.04	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Complier mean in alternative - Women	0.00	0.01	0.00	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N Clusters - Men	28,494	28,494	28,494	28,494	28,494
N Clusters - Women	15,778	15,778	15,778	15,778	15,778

Notes: This table shows reduced-form estimates of the effects for (a) men and (b) women of admission to the TE program on the probabilities of assignment to majors in Construction, Industry and Production, Computing, Engineering, or Other. Programs in the CINE-UNESCO TE category are classified using their OECD subclassification. Panel A uses the full sample of applicants in a margin of admission involving TE and a different field. Panel B uses the same sample, but weights observations in such a way that the distribution of women's applications mirrors that of men. Specifically, we weight women's observations by n^m_{jk}/n^f_{jk}, where n^g_{jk} is the number of gender g applicants with program j as the target program and program k as the fallback program. Conversely, Panel C weights men's observations by n^f_{jk}/n^m_{jk}. In Panels B and C, we focus exclusively on margins (j,k) with applicants of both genders. In all cases, observations are further weighted using a triangular kernel, with bandwidths optimally selected following Calonico et al. (2019). We also report the p-values for the null hypothesis that effects are the same for men and women, the estimated mean of the outcome for those assigned to the non-TE program, and the number of clusters. Standard errors are clustered at the individual level and shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F.3: Effects of TE Assignment on Assigned Program Attributes

	Characteristics of assigned programs					Peers Characteristics			
	Target program	Preference Rank program	Elite Inst.	Inst. Outside Home Region	Average Earnings Enr. Program	Peers Math	Peers Lang	Peers Avg	Peers Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(a) Admitted to TE - Men	-0.01^{**}	-0.00	-0.07^{***}	-0.02^{***}	$3,008^{***}$	11.74^{***}	-12.51^{***}	-0.39^{*}	0.15^{***}
	(0.00)	(0.02)	(0.00)	(0.00)	(65)	(0.28)	(0.25)	(0.22)	(0.00)
(a) Admitted to TE - Women	-0.05^{***}	0.09^{***}	-0.05^{***}	-0.03^{***}	$1,937^{***}$	11.16^{***}	-11.11^{***}	0.03	0.13^{***}
	(0.01)	(0.03)	(0.00)	(0.01)	(83)	(0.41)	(0.36)	(0.32)	(0.00)
p-val: (a)=(b)	[0.000]	[0.003]	[0.000]	[0.187]	[0.000]	[0.247]	[0.001]	[0.288]	[0.000]
Complier mean in alternative - Men	0.42^{***}	2.96^{***}	0.24^{***}	0.26^{***}	$21,100^{***}$	637.00^{***}	607.45^{***}	622.22^{***}	0.56^{***}
	(0.00)	(0.01)	(0.00)	(0.00)	(69)	(0.55)	(0.46)	(0.48)	(0.00)
Complier mean in alternative - Women	0.52^{***}	2.97^{***}	0.17^{***}	0.26^{***}	$18,555^{***}$	612.16^{***}	596.85^{***}	604.50^{***}	0.43^{***}
	(0.00)	(0.02)	(0.00)	(0.00)	(77)	(0.68)	(0.57)	(0.60)	(0.00)
N Clusters - Men	37,388	37,388	37,388	37,388	33,085	33,078	33,078	33,078	33,078
N Clusters - Women	20,062	20,062	20,062	20,062	18,245	18,228	18,228	18,228	18,228

Notes: This table shows reduced-form estimates of the effects of admission to the TE program on attributes of the assigned program for (a) men and (b) women. Considered outcomes are: the probability of assignment to the target program, the ranking of the assigned program, the probability of assignment to an elite institution, the probability of assignment to an institution outside their hometown region, the average earnings of graduates at the assigned program, and the average math and language test scores of peers at the assigned program. Estimates are obtained using the full sample of applicants in a margin of admission involving TE and a different field. Observations are weighted using a triangular kernel, with bandwidths optimally selected following Calonico et al. (2019). We also report the p-values for the null hypothesis that effects are the same for men and women, the estimated mean of the outcome for those assigned to the non-TE program, and the number of clusters. Standard errors are clustered at the individual level and shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F.4: Effect of Enrolling in TE on Earnings in 2018-2019 - Reweighted Estimates by Application Margin

	Alternative Field									
	All non-TE 100%		Science & Math 22%		Business 24%		Health 11%		Other non-TE 43%	
	earnings (1)	employment (2)	earnings (3)	employment (4)	earnings (5)	employment (6)	earnings (7)	employment (8)	earnings (9)	employment (10)
Panel A: Using male distribution of margins										
(a) Enrolls in TE - Men	$1,865^{***}$	0.029^{***}	$2,110^{*}$	0.026	$-1,206$	0.006	$-1,787$	-0.005	$4,090^{***}$	0.055^{**}
	(653.5)	(0.01)	(1,228)	(0.02)	(1,380)	(0.02)	(3,290)	(0.04)	(1,058)	(0.02)
(b) Enrolls in TE - Women	-307.5	0.004	1,821	0.037	$-2,092$	0.024	1,235	-0.177^{***}	1,051	-0.007
	(1,051)	(0.02)	(1,755)	(0.03)	(1,813)	(0.03)	(3,683)	(0.06)	(1,483)	(0.04)
p-val: (a)=(b)	[0.0792]	[0.2243]	[0.8926]	[0.7489]	[0.6977]	[0.6059]	[0.5407]	[0.0173]	[0.0953]	[0.1625]
Complier mean in alternative - Men	$25,138^{***}$	0.767^{***}	$28,625^{***}$	0.747^{***}	$31,152^{***}$	0.829^{***}	$29,552^{***}$	0.802^{***}	$16,774^{***}$	0.729^{***}
	(561.2)	(0.01)	(1,062)	(0.01)	(1,241)	(0.02)	(2,712)	(0.04)	(874.8)	(0.02)
Complier mean in alternative - Women	$23,362^{***}$	0.780^{***}	$23,242^{***}$	0.716^{***}	$28,471^{***}$	0.811^{***}	$24,555^{***}$	0.922^{***}	$16,938^{***}$	0.772^{***}
	(856.7)	(0.01)	(1,490)	(0.02)	(1,630)	(0.03)	(2,940)	(0.05)	(1,248)	(0.03)
First stage - Men	0.551^{***}	0.551^{***}	0.653^{***}	0.653^{***}	0.533^{***}	0.533^{***}	0.568^{***}	0.568^{***}	0.503^{***}	0.503^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
First stage - Women	0.576^{***}	0.576^{***}	0.688^{***}	0.688^{***}	0.480^{***}	0.480^{***}	0.529^{***}	0.529^{***}	0.480^{***}	0.480^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.02)	(0.02)
N Clusters - Men	25,673	25,673	6,629	6,629	6,684	6,684	2,398	2,398	9,418	9,418
N Clusters - Women	14,961	14,961	4,454	4,454	5,473	5,473	2,856	2,856	5,622	5,622
BW - Men	47.45	47.45	48.60	48.60	39.25	39.25	41.55	41.55	41.00	41.00
BW - Women	27.45	27.45	44.90	44.90	55.95	55.95	40.74	40.74	25.05	25.05
Panel B: Using female distribution of margins										
(a) Enrolls in TE - Men	665.7	0.006	$2,434^{**}$	0.023	$-2,280$	-0.021	-928.4	-0.035	$2,281^{*}$	0.023
	(710.4)	(0.02)	(1,228)	(0.03)	(1,419)	(0.03)	(3,545)	(0.06)	(1,198)	(0.03)
(b) Enrolls in TE - Women	-178.3	0.008	1,667	0.035	$-1,757$	0.035	-925.9	-0.088^{*}	726.1	-0.016
	(693.3)	(0.02)	(1,166)	(0.03)	(1,315)	(0.03)	(2,652)	(0.05)	(1,123)	(0.03)
p-val: (a)=(b)	[0.3952]	[0.9436]	[0.6508]	[0.7445]	[0.7866]	[0.1184]	[0.9996]	[0.4983]	[0.3436]	[0.3924]
Complier mean in alternative - Men	$21,678^{***}$	0.768^{***}	$22,075^{***}$	0.729^{***}	$28,297^{***}$	0.835^{***}	$25,606^{***}$	0.849^{***}	$16,068^{***}$	0.717^{***}
	(606.9)	(0.01)	(1,059)	(0.02)	(1,290)	(0.02)	(2,856)	(0.05)	(1,005)	(0.03)
Complier mean in alternative - Women	$19,631^{***}$	0.779^{***}	$18,274^{***}$	0.710^{***}	$25,311^{***}$	0.793^{***}	$22,420^{***}$	0.865^{***}	$15,436^{***}$	0.783^{***}
	(583.8)	(0.01)	(976.8)	(0.02)	(1,174)	(0.02)	(2,148)	(0.04)	(978.8)	(0.03)
First stage - Men	0.504^{***}	0.504^{***}	0.577^{***}	0.577^{***}	0.500^{***}	0.500^{***}	0.554^{***}	0.554^{***}	0.475^{***}	0.475^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
First stage - Women	0.517^{***}	0.517^{***}	0.583^{***}	0.583^{***}	0.463^{***}	0.463^{***}	0.510^{***}	0.510^{***}	0.457^{***}	0.457^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
N Clusters - Men	25,673	25,673	6,629	6,629	6,684	6,684	2,398	2,398	9,418	9,418
N Clusters - Women	14,961	14,961	4,454	4,454	5,473	5,473	2,856	2,856	5,622	5,622
BW - Men	47.45	47.45	48.60	48.60	39.25	39.25	41.55	41.55	41.00	41.00
BW - Women	27.45	27.45	44.90	44.90	55.95	55.95	40.74	40.74	25.05	25.05

Notes: This table shows 2SLS estimates of the effects for (a) men and (b) women of enrollment in TE. Odd columns show effects on average annual earnings during the 2018–2019 period and even columns show effects on the probability of having positive earnings for at least one month. Columns 1–2 use all applicants in a margin of admission involving TE and a different field. The remaining columns focus on subsamples of applicants with other specified fields as the alternative to TE. Panel A weights observations in such a way that the distribution of women's applications mirrors that of men. Specifically, we weight women's observations by n^m_{jk}/n^f_{jk}, where n^g_{jk} is the number of gender g applicants with program j as the target program and program k as the fallback program. Conversely, Panel B weights men's observations by n^f_{jk}/n^m_{jk}. In Panels A and B, we focus exclusively on margins (j,k) with applicants of both genders. In all cases, observations are further weighted using a triangular kernel, with bandwidths optimally selected following Calonico et al. (2019). We also report the p-values for the null hypothesis that effects are the same for men and women, the estimated mean of the outcome for compliers assigned to the non-TE program, the first-stage coefficients, and the number of clusters. Standard errors are clustered at the individual level and shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F.5: Effects of TE Assignment on Assigned Program Attributes for Women - TE as target program vs. TE as fallback program

	Characteristics of assigned programs					Peer Characteristics	
	Target program	Preference Rank program	Elite Inst.	Inst. Outside Home Region	Average Earnings Enr. Program	Peers Math	Peers Lang
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Admitted to TE $\times$:							
(a) TE $\succ$ Alt	0.97***	−1.59***	−0.01	−0.06***	3,197***	34.49***	9.95***
	(0.01)	(0.07)	(0.01)	(0.02)	(237)	(1.09)	(0.93)
(b) Alt $\succ$ TE	−0.98***	1.73***	−0.12***	−0.00	1,047***	−7.90***	−32.36***
	(0.01)	(0.06)	(0.01)	(0.01)	(181)	(0.92)	(0.77)
p-val: (a)=(b)	[0.000]	[0.000]	[0.000]	[0.015]	[0.000]	[0.000]	[0.000]
Complier mean in Alt:							
TE $\succ$ Alt	0.00	3.92***	0.18***	0.30***	18,099***	604.43***	588.02***
	(0.00)	(0.06)	(0.01)	(0.01)	(252)	(2.05)	(1.69)
Alt $\succ$ TE	0.98***	2.27***	0.19***	0.23***	18,856***	620.71***	606.40***
	(0.01)	(0.04)	(0.01)	(0.01)	(168)	(1.39)	(1.16)
N Clusters:							
TE $\succ$ Alt	7,517	7,517	7,517	7,517	6,793	6,746	6,746
Alt $\succ$ TE	12,545	12,545	12,545	12,545	11,452	11,482	11,482

Notes: This table reports reduced-form estimates of the effect of assignment to a TE program on the characteristics of the program individuals are assigned to and on the characteristics of their peers, separately by preference ordering. (a) corresponds to applicants who rank TE above the alternative program (TE $\succ$ Alt), while (b) corresponds to applicants who rank the alternative above TE (Alt $\succ$ TE). Columns (1)–(5) describe characteristics of the assigned program, including whether it is the target program, its preference rank, selectivity, geographic location, and average earnings of enrolled students. Columns (6)–(7) report peer characteristics in math and language. We also report p-values for tests of equality between (a) and (b), complier means for applicants assigned to the alternative program, and the number of clusters. Estimates are obtained using local linear regressions with triangular kernel and optimal bandwidths following Calonico et al. (2019). Observations are weighted using the corresponding optimal kernel weights. Standard errors are clustered at the individual level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table F.6: Effects of Enrollment in TE on Earnings: TE as target vs. TE as fallback

	Men	Women
	(1)	(2)
Enrolls in TE ×		
(a) TE≻Alt	$1,488$	$-2,549$
	$(1,185)$	$(1,573)$
(b) Alt≻TE	$1,764$	$2,380$
	$(1,162)$	$(1,527)$
p-val: (a)=(b)	[0.8681]	[0.0262]
Complier mean in Alt		
TE≻Alt	$26,408^{***}$	$20,955^{***}$
Alt≻TE	$21,073^{***}$	$17,501^{***}$
N Clusters		
TE≻Alt	15,971	7,409
Alt≻TE	21,267	12,477

Notes: This table reports 2SLS estimates of the effect of enrolling in a TE program on annual earnings, separately by gender and by preference ordering. (a) corresponds to applicants who rank TE above the alternative program (TE ≻ Alt), while (b) corresponds to applicants who rank the alternative above TE (Alt ≻ TE). Column (1) reports estimates for men and column (2) for women. We also report p-values for tests of equality between (a) and (b), complier means for applicants who enroll in the alternative program, and the number of clusters. Estimates are obtained using local linear regressions with a triangular kernel and optimal bandwidths following Calonico et al. (2019). Observations are weighted using the corresponding optimal kernel weights. Standard errors are clustered at the individual level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table F.7: Effect of Enrolling in TE on Earnings and Employment in 2018-2019 - Target and Fallback in the Same Institution

	Alternative Field									
	All non-TE		Science & Math		Business		Health		Other non-TE	
	earnings	employment	earnings	employment	earnings	employment	earnings	employment	earnings	employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(a) Enrolls in TE - Men	3,513***	0.033**	4,758***	0.050**	2,128	0.021	1,193	−0.041	4,657***	0.036
	(795.9)	(0.01)	(1,695)	(0.02)	(1,680)	(0.02)	(3,964)	(0.05)	(1,229)	(0.03)
(b) Enrolls in TE - Women	−145.7	0.001	2,402	0.018	−183.3	0.030	−3,044	−0.049	324.0	−0.026
	(917.8)	(0.02)	(1,484)	(0.04)	(1,613)	(0.03)	(3,130)	(0.06)	(1,615)	(0.05)
p-val: (a)=(b)	[0.0026]	[0.1851]	[0.2957]	[0.4424]	[0.3209]	[0.8111]	[0.4016]	[0.9257]	[0.0328]	[0.2426]
Complier mean in alternative - Men	23,461***	0.764***	28,010***	0.748***	28,537***	0.806***	28,156***	0.822***	14,409***	0.734***
	(657.4)	(0.01)	(1,327)	(0.02)	(1,435)	(0.02)	(3,339)	(0.04)	(999)	(0.02)
Complier mean in alternative - Women	19,217***	0.781***	17,005***	0.715***	23,253***	0.796***	23,911***	0.822***	14,579***	0.789***
	(767.2)	(0.02)	(1,139)	(0.03)	(1,462)	(0.03)	(2,551)	(0.05)	(1,440)	(0.04)
First stage - Men	0.545***	0.545***	0.673***	0.673***	0.525***	0.525***	0.564***	0.564***	0.488***	0.488***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)
First stage - Women	0.510***	0.510***	0.591***	0.591***	0.454***	0.454***	0.508***	0.508***	0.434***	0.434***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)
N Clusters - Men	19,124	19,124	3,961	3,961	5,150	5,150	1,646	1,646	7,038	7,038
N Clusters - Women	9,842	9,842	2,675	2,675	4,214	4,214	2,113	2,113	3,529	3,529
BW - Men	47.45	47.45	48.60	48.60	39.25	39.25	41.55	41.55	41.00	41.00
BW - Women	27.45	27.45	44.90	44.90	55.95	55.95	40.74	40.74	25.05	25.05

Notes: This table shows 2SLS estimates of the effects for (a) men and (b) women of enrolling in the TE cutoff program on earnings and employment in 2018–2019. We focus on the subsample of applicants with target and fallback programs in the same institution. Columns 1–2 use applicants in a margin of admission involving TE and a different field (in the same institution). The remaining columns focus on the subsamples of applicants with programs in other specified fields as the alternative to TE (also in the same institution). Estimates are obtained using local linear regressions with a triangular kernel and optimal bandwidths following Calonico et al. (2019). Observations are weighted using the corresponding optimal kernel weights. We also report: the p-values for the null hypothesis that effects are the same for men and women, the estimated mean of the outcome for compliers who enrolled in the non-TE cutoff program, the first-stage coefficients, and the number of clusters. Standard errors are clustered at the individual level and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table F.8: Effect of Enrolling in TE on Earnings in 2018-2019 - Reweighted Estimates by Math Test Scores

	Alternative Field									
	All non-TE		Science & Math		Business		Health		Other non-TE	
	earnings	employment	earnings	employment	earnings	employment	earnings	employment	earnings	employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Using male distribution of math test scores										
(a) Enrolls in TE - Men	1,954***	0.030***	2,679**	0.030*	−518.4	0.008	−2,472	−0.006	4,133***	0.054***
	(533.2)	(0.01)	(1,114)	(0.02)	(1,256)	(0.02)	(2,677)	(0.04)	(823.4)	(0.02)
(b) Enrolls in TE - Women	633.4	0.022	2,432*	0.053**	−1,037	0.029	2,277	−0.048	1,240	0.001
	(750.4)	(0.01)	(1,358)	(0.03)	(1,438)	(0.02)	(2,563)	(0.05)	(1,005)	(0.03)
p-val: (a)=(b)	[0.1515]	[0.6230]	[0.8883]	[0.4422]	[0.7858]	[0.4708]	[0.2002]	[0.4786]	[0.0260]	[0.0946]
Complier mean in alternative - Men	23,517***	0.767***	27,073***	0.748***	29,940***	0.825***	29,119***	0.809***	16,129***	0.729***
	(462.9)	(0.01)	(965.0)	(0.01)	(1,132)	(0.02)	(2,329)	(0.03)	(691.5)	(0.01)
Complier mean in alternative - Women	20,601***	0.763***	19,993***	0.698***	26,966***	0.803***	20,926***	0.814***	15,745***	0.767***
	(606.0)	(0.01)	(1,118)	(0.02)	(1,273)	(0.02)	(2,035)	(0.04)	(879.2)	(0.02)
First stage - Men	0.518***	0.518***	0.624***	0.624***	0.508***	0.508***	0.560***	0.560***	0.478***	0.478***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
First stage - Women	0.527***	0.527***	0.610***	0.610***	0.466***	0.466***	0.500***	0.500***	0.461***	0.461***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
N Clusters - Men	37,238	37,238	8,122	8,122	8,156	8,156	3,636	3,636	15,913	15,913
N Clusters - Women	19,886	19,886	5,356	5,356	6,532	6,532	4,142	4,142	8,473	8,473
BW - Men	47.45	47.45	48.60	48.60	39.25	39.25	41.55	41.55	41.00	41.00
BW - Women	27.45	27.45	44.90	44.90	55.95	55.95	40.74	40.74	25.05	25.05
Panel B: Using female distribution of math test scores										
(a) Enrolls in TE - Men	1,653***	0.030***	2,280**	0.024	−730.9	0.004	−2,150	−0.014	3,574***	0.057***
	(489.0)	(0.01)	(1,027)	(0.02)	(1,134)	(0.02)	(2,528)	(0.04)	(771.3)	(0.02)
(b) Enrolls in TE - Women	161.1	0.018	1,633	0.040	−1,639	0.030	1,885	−0.022	900.6	−0.003
	(599.7)	(0.01)	(1,072)	(0.02)	(1,206)	(0.02)	(2,156)	(0.04)	(905.8)	(0.03)
p-val: (a)=(b)	[0.0538]	[0.4873]	[0.6629]	[0.6168]	[0.5833]	[0.3997]	[0.2246]	[0.8931]	[0.0247]	[0.0650]
Complier mean in alternative - Men	20,561***	0.766***	23,777***	0.748***	26,030***	0.825***	27,399***	0.819***	15,031***	0.727***
	(419.8)	(0.01)	(896.8)	(0.02)	(1,006)	(0.02)	(2,232)	(0.03)	(633.0)	(0.02)
Complier mean in alternative - Women	18,655***	0.769***	17,769***	0.711***	24,388***	0.797***	20,049***	0.812***	14,816***	0.768***
	(505.5)	(0.01)	(897.2)	(0.02)	(1,084)	(0.02)	(1,783)	(0.04)	(786.0)	(0.02)
First stage - Men	0.485***	0.485***	0.581***	0.581***	0.484***	0.484***	0.555***	0.555***	0.457***	0.457***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
First stage - Women	0.490***	0.490***	0.561***	0.561***	0.442***	0.442***	0.479***	0.479***	0.438***	0.438***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
N Clusters - Men	37,238	37,238	8,122	8,122	8,156	8,156	3,636	3,636	15,913	15,913
N Clusters - Women	19,886	19,886	5,356	5,356	6,532	6,532	4,142	4,142	8,473	8,473
BW - Men	47.45	47.45	48.60	48.60	39.25	39.25	41.55	41.55	41.00	41.00
BW - Women	27.45	27.45	44.90	44.90	55.95	55.95	40.74	40.74	25.05	25.05

Notes: This table shows 2SLS estimates of the effects for (a) men and (b) women of enrollment in TE. Odd columns show effects on average annual earnings during the 2018–2019 period and even columns show effects on the probability of having positive earnings for at least one month. Columns 1–2 use all applicants in a margin of admission involving TE and a different field. The remaining columns focus on subsamples of applicants with other specified fields as the alternative to TE. Panel A weights observations in such a way that the distribution of women's math scores mirrors that of men's math scores. Specifically, we round math scores to the nearest 20% and weight women's observations by n_s^m/n_s^f, where n_s^g is the number of gender g applicants with math test scores in group s. Conversely, Panel B weights men's observations by n_s^f/n_s^m. In all cases, observations are further weighted using a triangular kernel, with bandwidths optimally selected following Calonico et al. (2019). We also report the p-values for the null hypothesis that effects are the same for men and women, the estimated mean of the outcome for compliers assigned to the non-TE program, the first-stage coefficients, and the number of clusters. Standard errors are clustered at the individual level and shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

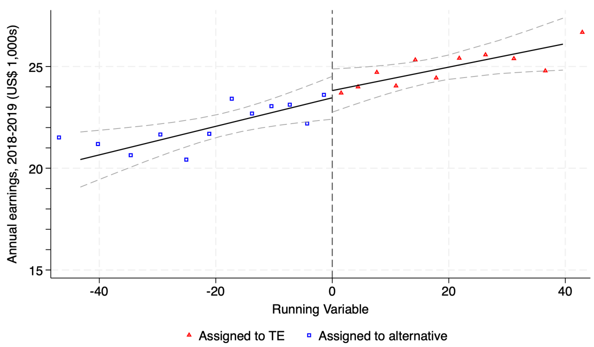
G Construction of RD Figures

This appendix explains the logic behind the RD figures in the paper. We start from two underlying samples: applicants for whom TE is the target field (so crossing the cutoff implies assignment to TE) and applicants for whom TE is the fallback field (so crossing the cutoff implies assignment away from TE). We then show how these two samples are pooled and transformed into the figure used in the main text. The purpose is to make clear how the pooled graph relates to the reduced-form regressions in equation (2) and to the alternative specifications discussed in Appendix F.

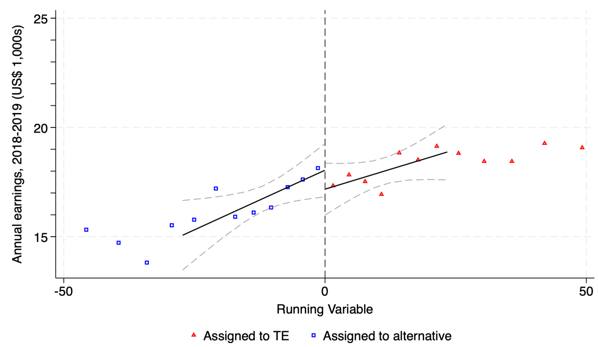
1. Separate RD plots by applicant type. A useful starting point is to separate applicants into two groups: (i) applicants for whom TE is the target field and (ii) applicants for whom TE is the fallback field. Within each group, one can draw standard RD plots using the original running variable r_{ij} (distance to the target-program cutoff) and the raw outcome Y_{ij}. Figure G.1 provides the intended layout for these conventional plots.

Figure G.1: Conventional RD Plots by Applicant Type

TE as Target

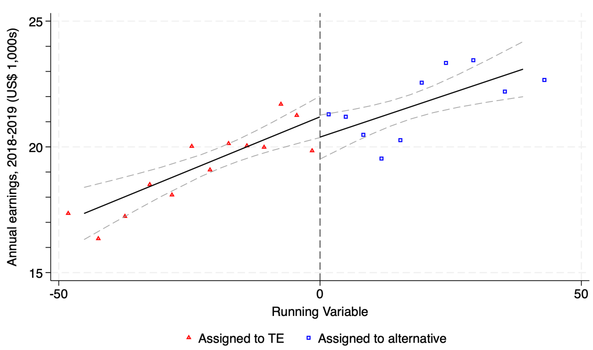


(a) Men

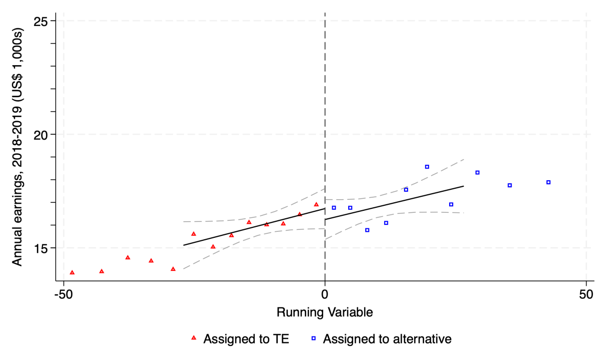


(b) Women

TE as Fallback



(c) Men



(d) Women

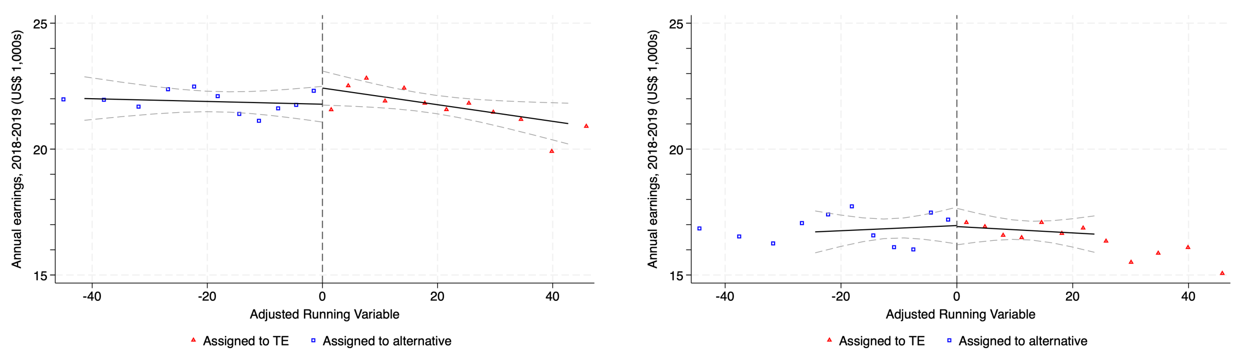
This figure shows standard RD plots separately by applicant type. In each panel, the horizontal axis is the original running variable $r_{ij} = s_i - c_j$ and the vertical axis shows raw annual earnings. Flexible fitted slopes can be used in the usual way. These plots serve as a familiar starting point before pooling the two samples.

2. Pooling the two samples and redefining the running variable. In the TE-target sample, crossing the cutoff implies assignment to TE, while in the TE-fallback sample crossing the cutoff implies assignment away from TE. Thus, when we pool the two samples, the sign of the assignment change at the cutoff is not the same across applicants. To give the pooled horizontal axis a common interpretation, let $A_j = \mathbb{1}(j \in TE)$ indicate whether the target program belongs to TE and define the transformed running variable

$$R_{ij} = r_{ij} \times (2A_j - 1),$$

so that $R_{ij} > 0$ always corresponds to assignment to TE. Once the horizontal axis is redefined, we can pool both applicant types and plot the raw outcome against R_{ij}. Figure G.2 provides the intended layout for this pooled raw plot.

Figure G.2: Pooled RD Plot with Transformed Running Variable R



(a) Men **(b)** Women

This figure shows the pooled raw RD plot using the transformed running variable R, defined so that values to the right of the cutoff correspond to assignment to TE for all applicants. This plot is useful for visualization but does not, in general, coincide exactly with the reduced-form coefficient estimated in equation (2).

3. Aligning RD plots with the reduced-form specification. The reduced-form regressions include target-program fixed effects and a specific functional-form adjustment in the running variable. Therefore, the visual jump in the pooled raw plot need not be numerically identical to the regression coefficient unless the figure is constructed to partial out those components. For exposition, suppressing gender and application-year subscripts, the pooled reduced-form regression underlying the flexible 4-slopes specification (as presented in Appendix F) can be written as

$$y_{ij} = \tau TE^a_{ij} + \delta_1 r_{ij} + \delta_2 (TE^a_{ij} \times r_{ij}) + \delta_3 (A_j \times r_{ij}) + \delta_4 (A_j \times TE^a_{ij} \times r_{ij}) + \mu_j + \varepsilon_{ij}.$$

This model allows for different slopes at both sides of the cutoff and for both groups (TE target and TE fallback). In this parameterization, δ_3 and δ_4 capture any difference in slopes between both groups. Using $R_{ij} = r_{ij}(2A_j - 1)$, this same specification can be re-written as

$$y_{ij} = \underbrace{\tau TE^a_{ij} + \rho R_{ij} + \phi(TE^a_{ij} \times R_{ij})}_{\text{Conventional RD in } R} + \underbrace{\pi r_{ij} + \lambda(TE^a_{ij} \times r_{ij}) + \mu_j}_{\text{controls}} + \varepsilon_{ij},$$

possibly augmented with additional controls in the specifications that include them. The two formulations are algebraically equivalent, with parameter mapping

$$\delta_1 = \pi - \rho, \qquad \delta_2 = \lambda - \phi, \qquad \delta_3 = 2\rho, \qquad \delta_4 = 2\phi.$$

In this representation, the terms involving r_{ij} and $TE^a_{ij} \times r_{ij}$ (together with μ_j) are controls, while the coefficients on R_{ij} and $TE^a_{ij} \times R_{ij}$ capture the differential slopes in r_{ij} between applicants for whom TE is the target field and those for whom TE is the fallback field. Our baseline 2-slopes specification is a restriction of this model, imposing $\delta_3 = \delta_4 = 0$ in the first formulation above (equivalently, $\rho = \phi = 0$ in the R-based representation).

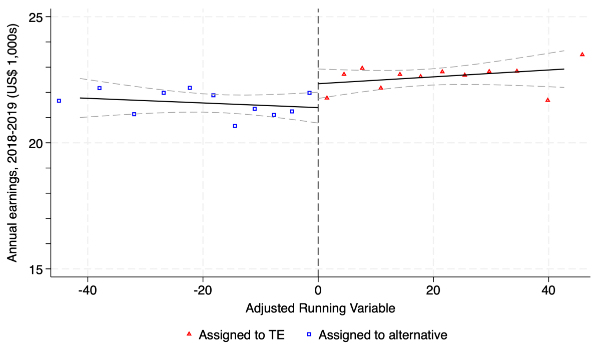
4. Constructing plots that mirror the reduced-form estimate. We build these figures in three steps. First, estimate the corresponding reduced-form specification (2-slopes or 4-slopes). Second, construct the adjusted outcome

$$\tilde{y}_{ij} = y_{ij} - \widehat{\pi} r_{ij} - \widehat{\lambda}(TE^a_{ij} \times r_{ij}) - \widehat{\mu}_j + C,$$

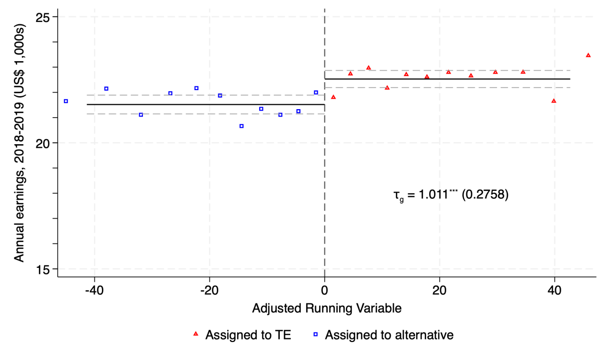
where C is a constant equal to the mean predicted outcome for untreated applicants at the cutoff, which in this notation is the average of $\widehat{\mu}_j$ across target programs. This subtracts the estimated controls while adding back a constant so that the adjusted outcome preserves levels at the cutoff. Third, plot $\tilde{y}_{ij}$ against R_{ij} and add fitted lines implied by the estimated coefficients on R_{ij} and $TE^a_{ij} \times R_{ij}$. Under the 2-slopes model, the fitted lines are flat by construction. Figure G.3 provides the intended layout for the annual-earnings comparison between adjusted outcomes under 4-slopes and 2-slopes.

Figure G.3: Coefficient-Mirroring RD Plots under 4-slopes and 2-slopes

Men

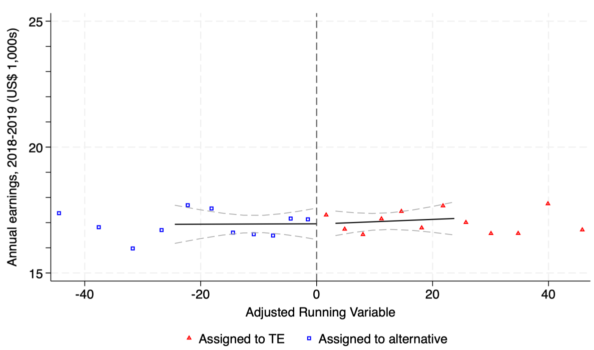


(a) Adjusted (4-slopes)

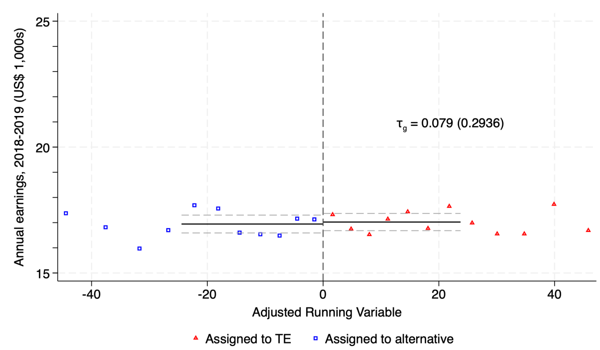


(b) Adjusted (2-slopes)

Women



(c) Adjusted (4-slopes)



(d) Adjusted (2-slopes)

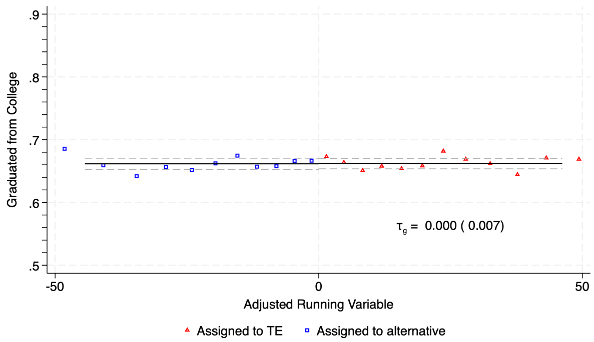
This figure compares, for annual earnings, the adjusted-outcome RD plots based on the flexible 4-slopes specification and the baseline 2-slopes specification used in the main text. The pooled raw RD plot with the transformed running variable *R* is shown separately in Figure G.2.

H Additional Results

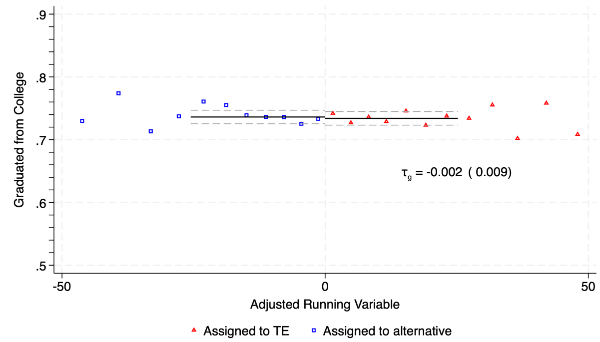
This section presents RD graphs showing the effects of crossing the threshold for a TE program on graduation, employment, fertility, and marriage (Figures H.1, H.2, and H.3).

Figure H.1: Effects of Assignment to TE on Graduation Outcomes

College Graduation

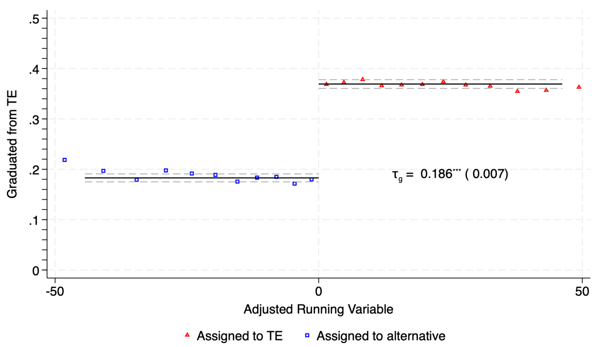


(a) Men

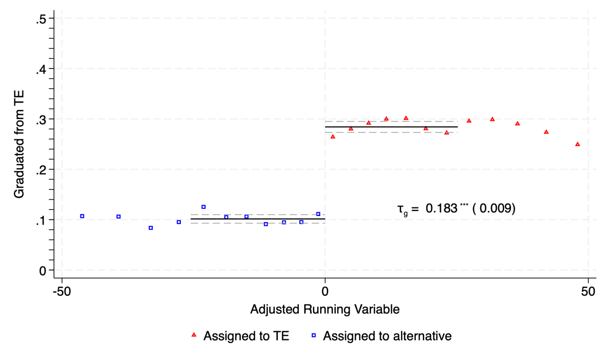


(b) Women

Graduation from TE



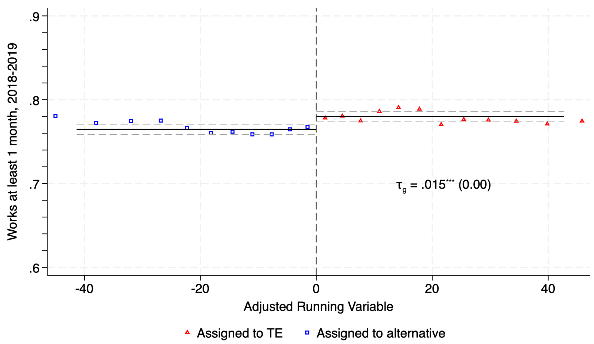
(c) Men



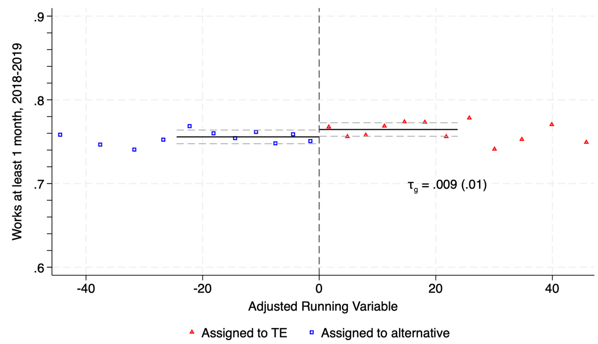
(d) Women

This figure shows, for men and women, the reduced-form effect of assignment to TE on college graduation and graduation from a TE field. The running variable is adjusted so that values to the right of the cutoff correspond to assignment to TE for all applicants. Dots represent average values of an adjusted outcome, constructed by removing the contribution of test scores, covariates, and fixed effects implied by the reduced-form specification in equation (2), estimated on the pooled sample using observations within the optimally selected bandwidth around the cutoff. This adjustment ensures that the figure visualizes the same object identified by the regression model. Solid lines and confidence intervals then summarize the adjusted outcome on each side of the cutoff, imposing flatness so that the visual discontinuity corresponds exactly to the reduced-form estimate.

Figure H.2: Effects of Enrollment in TE on Employment, 2018-2019



(a) Men

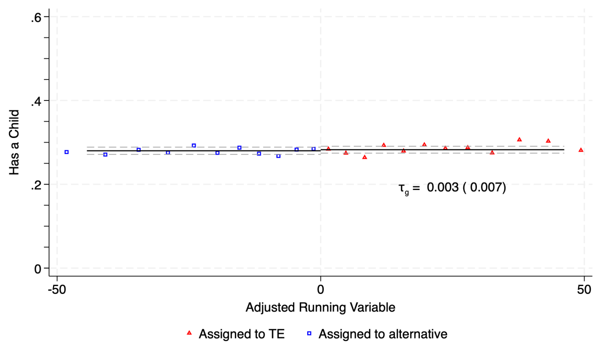


(b) Women

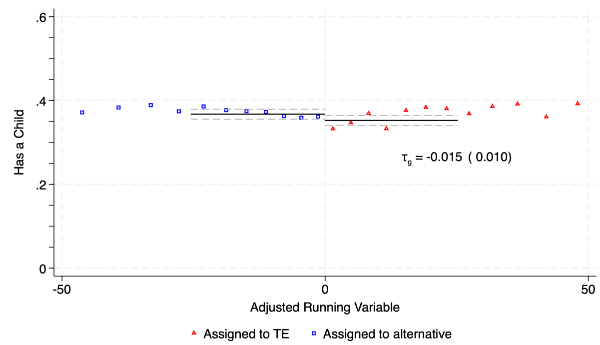
This figure shows, for (a) men and (b) women, the reduced-form effect of assignment to TE on the probability of working at least one month in the 2018-2019 period. The running variable is adjusted so that values to the right of the cutoff correspond to assignment to TE for all applicants. Dots represent average values of an adjusted outcome, constructed by removing the contribution of test scores, covariates, and fixed effects implied by the reduced-form specification in equation (2), estimated on the pooled sample using observations within the optimally selected bandwidth around the cutoff. This adjustment ensures that the figure visualizes the same object identified by the regression model. Solid lines and confidence intervals then summarize the adjusted outcome on each side of the cutoff, imposing flatness so that the visual discontinuity corresponds exactly to the reduced-form estimate.

Figure H.3: Effects of Assignment to TE on Fertility and Marriage

Fertility

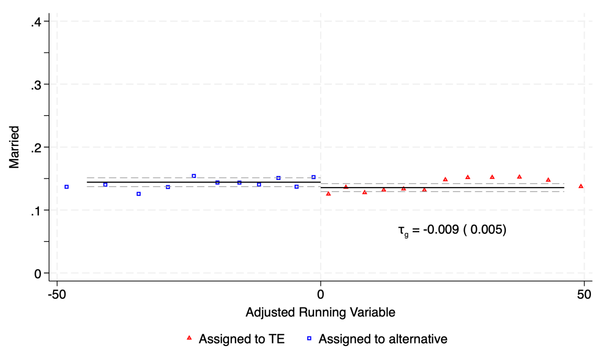


(a) Men

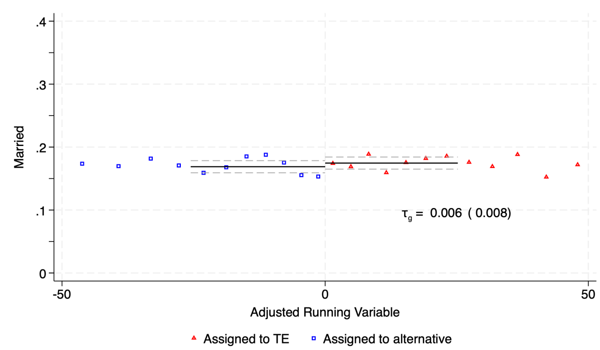


(b) Women

Marriage



(c) Men



(d) Women

This figure shows, for men and women, the reduced-form effect of assignment to TE on the probability of having a child and the probability of having a partner. The running variable is adjusted so that values to the right of the cutoff correspond to assignment to TE for all applicants. Dots represent average values of an adjusted outcome, constructed by removing the contribution of test scores, covariates, and fixed effects implied by the reduced-form specification in equation (2), estimated on the pooled sample using observations within the optimally selected bandwidth around the cutoff. This adjustment ensures that the figure visualizes the same object identified by the regression model. Solid lines and confidence intervals then summarize the adjusted outcome on each side of the cutoff, imposing flatness so that the visual discontinuity corresponds exactly to the reduced-form estimate.

I Additional Survey Results

Tables I.1 and I.2 show how survey respondents compare to students in our RD sample. Table I.3 reports survey responses on questions related to current employment.

Table I.1: Survey: Sample Description

	RD Sample	Survey											
		Men						Women					
		All	TE	Science	Business	Health	Other	All	TE	Science	Business	Health	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Age	36.10	35.50	35.66	36.32	33.09	35.50	36.28	35.67	35.57	35.76	34.35	35.73	35.95
Has Children	0.46	0.44	0.46	0.45	0.39	0.51	0.43	0.51	0.49	0.44	0.41	0.54	0.53
University Selectivity	598.38	624.24	614.53	637.84	639.01	624.72	624.50	624.45	623.18	634.94	626.06	622.34	624.86
Observations	49,935	1,526	491	96	259	141	528	2,289	234	125	301	368	1,238

Notes: This table shows information on age, probability of having children, and selectivity on the institution attended (where we take the average math and language score of students who enrolled in that institution in 2007 as a measure of selectivity) for individuals in our RD sample and individuals in our survey sample. The data comes from a survey that we designed and administered. The survey was sent by email by 14 of the 25 institutions participating in the centralized system of admission to former students who enrolled between 2000 and 2008.

Table I.2: Survey: Institutions Attended by Survey Respondents

Institution	Survey Sample	RD Sample
PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE	0.21	0.06
PONTIFICIA UNIVERSIDAD CATÓLICA DE VALPARAÍSO	0.00	0.05
UNIVERSIDAD ARTURO PRAT	0.02	0.01
UNIVERSIDAD AUSTRAL DE CHILE	0.00	0.03
UNIVERSIDAD CATÓLICA DE LA SANTÍSIMA CONCEPCIÓN	0.01	0.03
UNIVERSIDAD CATÓLICA DE TEMUCO	0.01	0.01
UNIVERSIDAD CATÓLICA DEL MAULE	0.01	0.01
UNIVERSIDAD CATÓLICA DEL NORTE	0.00	0.02
UNIVERSIDAD DE ANTOFAGASTA	0.00	0.01
UNIVERSIDAD DE ATACAMA	0.00	0.00
UNIVERSIDAD DE CHILE	0.16	0.09
UNIVERSIDAD DE CONCEPCIÓN	0.29	0.08
UNIVERSIDAD DE LA FRONTERA	0.00	0.03
UNIVERSIDAD DE LA SERENA	0.00	0.02
UNIVERSIDAD DE LOS LAGOS	0.04	0.01
UNIVERSIDAD DE MAGALLANES	0.00	0.00
UNIVERSIDAD DE PLAYA ANCHA DE CIENCIAS DE LA EDUCACIÓN	0.00	0.02
UNIVERSIDAD DE SANTIAGO DE CHILE	0.00	0.07
UNIVERSIDAD DE TALCA	0.01	0.02
UNIVERSIDAD DE TARAPACA	0.01	0.01
UNIVERSIDAD DE VALPARAÍSO	0.00	0.05
UNIVERSIDAD DEL BÍO-BÍO	0.00	0.05
UNIVERSIDAD METROPOLITANA DE CIENCIAS DE LA EDUCACIÓN	0.00	0.01
UNIVERSIDAD TECNOLÓGICA METROPOLITANA	0.05	0.05
UNIVERSIDAD TÉCNICA FEDERICO SANTA MARÍA	0.02	0.05
OTHER	0.16	0.21
Obs	3,815	49,935

Notes: This table shows the institution attended by individuals in our RD sample and individuals in our survey sample. The data comes from a survey that we designed and administered. The survey was sent by email by 14 of the 25 institutions participating in the centralized system of admission to former students who enrolled between 2000 and 2008.

Table I.3: Survey: Employment

	Men						Women					
	All (1)	TE (2)	Science (3)	Business (4)	Health (5)	Others (6)	All (7)	TE (8)	Science (9)	Business (10)	Health (11)	Others (12)
Employment status												
Dependent	0.79	0.84	0.73	0.76	0.79	0.76	0.78	0.81	0.70	0.79	0.86	0.75
Self-employed	0.13	0.10	0.12	0.10	0.16	0.18	0.13	0.07	0.18	0.09	0.10	0.16
Does not work	0.08	0.07	0.15	0.14	0.04	0.06	0.09	0.12	0.12	0.11	0.04	0.09
Observations	1,526	491	96	259	141	528	2,289	234	125	301	368	1,238
Main work												
Self-employed	0.12	0.09	0.17	0.10	0.11	0.16	0.12	0.05	0.15	0.10	0.08	0.14
Management position	0.28	0.40	0.16	0.30	0.18	0.22	0.21	0.30	0.13	0.34	0.12	0.19
Professional without people in charge	0.45	0.37	0.50	0.48	0.45	0.49	0.50	0.48	0.59	0.47	0.43	0.53
Professional with people in charge	0.15	0.14	0.17	0.12	0.26	0.13	0.17	0.17	0.14	0.09	0.37	0.14
Observations	1,405	458	82	222	135	497	2,082	205	110	267	352	1,126
Employment characteristics												
Hours per work day	8.89	8.95	9.07	8.79	9.25	8.77	8.55	8.74	8.44	8.58	8.88	8.42
Earnings	2,773	3,175	2,654	2,886	3,148	2,272	2,124	2,773	1,911	2,652	2,430	1,817
Observations	1,405	458	82	222	135	497	2,082	205	110	267	352	1,126
Employment Sector												
Agriculture & Fishing	0.06	0.04	0.02	0.04	0.00	0.10	0.02	0.04	0.03	0.02	0.00	0.03
Mining	0.04	0.07	0.07	0.01	0.01	0.02	0.01	0.08	0.05	0.00	0.00	0.00
Manufacture	0.03	0.06	0.04	0.03	0.01	0.01	0.02	0.07	0.04	0.04	0.01	0.01
Electricity Gas Water	0.03	0.07	0.02	0.01	0.00	0.01	0.02	0.07	0.03	0.03	0.00	0.01
Construction	0.07	0.12	0.00	0.02	0.00	0.06	0.03	0.12	0.01	0.01	0.00	0.02
Commerce	0.05	0.07	0.02	0.11	0.01	0.02	0.04	0.05	0.01	0.12	0.01	0.02
Hotels and Rest.	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Transport and Storage	0.05	0.08	0.01	0.04	0.00	0.03	0.03	0.07	0.00	0.07	0.00	0.02
Finance	0.05	0.06	0.04	0.14	0.00	0.01	0.02	0.05	0.01	0.10	0.00	0.01
Real Estate	0.02	0.03	0.01	0.04	0.00	0.02	0.01	0.03	0.01	0.02	0.00	
Public Sector	0.05	0.10	0.05	0.20	0.04	0.13	0.11	0.06	0.09	0.18	0.01	0.13
Education	0.20	0.10	0.46	0.14	0.07	0.31	0.31	0.14	0.45	0.15	0.11	0.43
Health y Social Service	0.12	0.03	0.05	0.02	0.83	0.08	0.23	0.05	0.08	0.06	0.83	0.13
Other Sevices	0.14	0.17	0.10	0.14	0.02	0.15	0.10	0.10	0.16	0.12	0.01	0.11
Observations	1,405	458	82	222	135	497	2,082	205	110	267	352	1,126

Notes: This table shows information on employment for men and women who pursued a career in TE, business, health, Science and other fields. The data comes from a survey that we designed and administered. The survey was sent by email by 14 of the 25 institutions participating in the centralized system of admission to former students who enrolled between 2000 and 2008.