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The Effects of Educational Supports for the "Missing One-Offs" in Vocational High Schools

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A growing body of evidence suggests that vocationally focused programs of study substantially improve high-school completion and longer-run economic success. However, the corresponding recommendations to expand vocational programs may have unintended, negative consequences for low-income, academically successful students (i.e., the "missing one offs") who have the capacity and motivation to attend highly selective universities. This study contributes to our understanding of these issues by examining an innovative, college-preparatory program targeted to academically successful Chilean students attending vocational high schools serving lower-income communities. This program (Escuela Desarrollo de Talentos or EDT) provides academic and social-emotional supports aligned with admission to selective universities. We examine the educational effects of EDT participation using a fuzzy regression-discontinuity design based on its eligibility rules. We find that the EDT program did not increase the probability of graduating from high school but did increase performance in math courses. We also find corresponding evidence suggesting that EDT participation increased math performance on college entrance exams and shifted students away from further postsecondary vocational training and towards matriculation at elite universities.

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The Effects of Educational Supports for the "Missing One-Offs" in Vocational High Schools

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Abstract

A growing body of evidence suggests that vocationally focused programs of study substantially improve high-school completion and longer-run economic success. However, the corresponding recommendations to expand vocational programs may have unintended, negative consequences for low-income, academically successful students (i.e., the "missing one offs") who have the capacity and motivation to attend highly selective universities. This study contributes to our understanding of these issues by examining an innovative, college-preparatory program targeted to academically successful Chilean students attending vocational high schools serving lower-income communities. This program (*Escuela Desarrollo de Talentos* or EDT) provides academic and social-emotional supports aligned with admission to selective universities. We examine the educational effects of EDT participation using a fuzzy regression-discontinuity design based on its eligibility rules. We find that the EDT program did not increase the probability of graduating from high school but did increase performance in math courses. We also find corresponding evidence suggesting that EDT participation increased math performance on college entrance exams and shifted students away from further postsecondary vocational training and towards matriculation at elite universities.

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1. Introduction

A growing body of empirical evidence (e.g., Kemple and Willner, 2008; Brunner, Dougherty and Ross, 2019; Dougherty, 2018; Edmunds et al, 2012; Berger et al, 2014) suggests that well-designed, vocationally focused secondary programs of study can have substantial positive effects both on students' near-term educational attainment and on longer-run economic success. For example, Kemple and Willner (2008) find that random assignment to a career academy increases earnings by 11 percent. Other carefully identified studies also find evidence that vocational high schools increased the probability of high-school graduation (e.g., Dougherty, 2018; Hemelt, Lenard and Paeplow, 2019). Based in part on such evidence, Cullen et al. (2013) argue that vocationally focused high school programs are chronically underutilized in the U.S. Compellingly, they note that, while the vast majority of U.S. high schools have a traditional, academic, college-preparatory focus, most students will *not* complete a college degree within six years of their on-time high-school graduation.[1]

One fundamental concern with the recommendation to expand vocational education is that it may exacerbate educational inequality for an important subset of students. Current opportunities for vocational training are concentrated among students from socioeconomically disadvantaged backgrounds. A reasonable concern is that the expanded availability of such programs would increasingly redirect lower-income students who are academically talented and motivated away from highly selective post-secondary opportunities. Recent empirical evidence has underscored the unique educational challenges faced by the "hidden supply" of such students. Hoxby and Avery (2013) describe such high-achieving but lower-income students as "missing one offs" and present striking evidence that they tend to pursue the less-selective post-secondary opportunities that their peers do rather than options consistent with their capability.

These important challenges in the design of educational systems provide the context for this study. Specifically, this study discusses and examines a small but innovative Chilean program that identified high-performing students in seven vocational high schools serving low-income communities and prepared them to meet the rigid admissions requirements of

[1] For example, the high school graduation rate for public schools is 83 percent, while the college matriculation rate is only 44 percent (U.S. Department of Education, 2017). Among these college matriculants, only 59 percent are expected to complete a bachelor's degree within six years. This implies that, on average, only 22 percent of a high school cohort will complete college within six years of their on-time high-school graduation.

Chile's top-tier universities. This program – *Escuela Desarrollo de Talentos* (EDT) – began in 2013 and is managed by one of Chile's most selective universities, the University of Chile. This free two-year program serves 11th and 12th grade students with 10 to 12 hours of classes per week that supplement their standard high school curriculum. The EDT program, which we describe in more detail below, focuses on core academic subjects (i.e., mathematics and language arts) as well as educationally relevant social-emotional skills (e.g. perseverance, critical thinking, curiosity).

We use unusually rich longitudinal data on the educational trajectories of students in these high schools to examine the effects of the EDT program. We acquired these restricted-use student-level data through a partnership with Chile's Ministry of Education. Our outcome measures focus on three distinct stages relevant to the transition from high school to a selective university. First, we examine the impact of EDT eligibility on the probability of graduating from high school and on measures of academic performance (i.e., GPA) during 11th and 12th grades. Second, we focus on the probability of taking the entrance exams required for admission to selective universities as well as performance on these exams. And, third, we measure student matriculation into the varied options for post-secondary education in Chile.[2] We identify the effects of the EDT program on these outcomes using a fuzzy regression discontinuity (RD) design. This RD design leverages the strict EDT eligibility rule that required students to have an overall GPA based on grades 9 and 10 that exceeded school-specific thresholds. This eligibility rule implies that only 11 percent of the total sample was eligible for EDT participation. In general, we find that EDT eligibility led to substantial improvements on several of these educational outcomes (e.g., high-school GPA in mathematics, matriculation at elite universities). We conclude with a discussion of the implications of these findings.

2. The Chilean Context and the EDT Program

Chile is a middle-income country and a member of the Organization for Economic Cooperation and Development (OECD). Chile has levels of educational attainment broadly similar to those in the United States. The system of schooling in Chile is also highly segregated

[2] A fourth relevant outcome concerns persistence and completion in universities. Because university degrees in Chile take at least 5 to 6 years to complete, we are not yet able to observe these outcomes in the data.

and has several distinctive institutional features. For example, roughly 40 percent of high school students, predominantly those from poorer families, attend public schools (i.e., *colegios públicos*) that receive per-student public subsidies and are run by local municipalities. Another 51 percent of high-school students (i.e., largely those from middle-class families) attend "private-subsidized" schools (i.e., *colegios particulares-subvencionados*). These schools are privately owned and operated, but financed by a public per-student subsidy and, in some cases, supplemented with fees paid by parents. The remaining 9 percent of high school students who are largely from wealthy families attend private schools (i.e, *colegios privados*) that rely exclusively on fees. In addition, some high schools focus exclusively on college-preparatory curricula (i.e. *colegios humanista-científicos*). In contrast, vocational high schools share these curricula, which are defined by the Ministry of Education, only during 9^{th} and 10^{th} grades. In 11^{th} and 12^{th} grades, the students at vocational high schools focus on job-oriented training. Students generally choose a high school that is in their neighborhood and, critically, vocational high schools tend to be located in poorer neighborhoods. Over 99 percent of vocational high schools are public or private-subsidized. That is, virtually *no* private schools focus on vocational training.

High school graduates in Chile have three broad options for further postsecondary education. Technical training centers generally offer two-year programs with a vocational focus. Professional learning institutes offer longer programs (i.e., often 4 years) that focus on higher-level professional training (i.e., but not academic degrees). Degree-conferring universities in Chile require 5 to 6 years of study depending on the major. Eight traditional universities in Chile (i.e., those existing before 1981 reforms) in addition to other 21 universities are members of the Council of Rectors of Universities of Chile (CRUCH). The CRUCH universities are generally more prestigious and selective, though there is also variation among them.[3] The CRUCH universities can also be uniquely attractive to low-income students because they provide more financial aid. The 29 CRUCH universities admit students under a centralized admissions process based on entrance-exam scores.[4] Specifically, students apply to

[3] According to the Academic Ranking of World Universities (ARWU), the top-two Chilean universities are *Universidad de Chile* (a public university) and *Pontificia Universidad Católica de Chile* (a private Catholic university). Both institutions are CRUCH members. The non-CRUCH universities are private, generally less selective, and practice open-admissions policies. Only twelve private universities are CRUCH members and participate in the centralized admissions process described here.

[4] The university entrance exam (called *Prueba de Selección Universitaria*, PSU) is equivalent to the SAT in the U.S. The exam consists of two mandatory tests, one in mathematics and one in language, as well as two subject tests

as many as 10 major-institution combinations. The universities participating in this centralized admission process combine each student's university entrance-exam scores on these tests (i.e., in proportions depending on the major they choose) with their cumulative GPA from high school to produce the weighted score used to determine admission to each major and institution. In this highly structured, test-based system, students who, for whatever reason, attend a vocational high school are at a considerable disadvantage with regard to attending universities, particularly the more selective ones.

The *Escuela Desarrollo de Talentos* (EDT) is an academic program that aims to mitigate the profound inequalities in access to higher education that exist in Chile. In particular, this program provides opportunities for academically promising but low-income high-school students attending vocational high schools to develop the necessary skills to gain entrance to and to graduate successfully from Chile's highly selective universities. The EDT's academic program consists of a rigorous curriculum in mathematics, and language that is taught by university professors and designed to align the high-school curricula with first year of college. The EDT curricula also seeks to build socioemotional skills related to traits such as perseverance, critical thinking, and curiosity. More generally, the EDT program also supports college readiness by providing students with opportunities to learn about colleges, financial aid, and campus life. University students serve as EDT teaching assistants and provide more personalized attention and support. The EDT program also includes a psychologist who is available to students who could benefit from mental-health supports.

Students participate in this two-year program for free, during their 11th and 12th grades. Classes are held at the facilities of the School of Economics and Business at the University of Chile a weekday after school and on Saturdays for a total of 10-12 hours per week. The program had an annual cost of approximately US$1,600 per student in 2015 dollars.[5] For the first cohorts of students, the School of Economics and Business bore the entire cost of the program. Subsequent cohorts have been funded both by private and public donations and by the School of Economics and Business.

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in science and social sciences. All institutions participating in centralized admissions commit to not accepting students with weighted average PSU scores below 450 and most selective institutions set minimum scores above 600.

[5] As a frame of reference, the annual spending in Chilean vocational high schools (at purchasing power parity) is roughly US$4,500 per student in 2015.

We examine the impact of this program using student-level, longitudinal data from seven vocational high schools in Santiago, Chile who partnered to offer the EDT program in its first year (i.e., starting in 2013).[6] Prior to the beginning of the program, these high schools provided the students' academic records to the EDT staff for 9th and 10th grades. The EDT program used these data to identify and recruit program-eligible students. This recruitment and selection took place at the end of the 2012 academic year, when students were finishing 10th grade. Students were eligible for the EDT program if their average GPA in 9th and 10th grades (i.e., *before* their vocational education began) were above school-specific cutoffs set by the EDT program.

The "intent to treat" (ITT) sample across these seven schools consists of the 1,003 students who were enrolled in the high school at the end of 10th grade. The program-eligible subset of these students (ITT = 1) consists of those whose baseline GPA exceeded a cutoff score defined for each school (n = 111). Each student's baseline GPA, centered on their school-specific cutoff, is the assignment variable used in the regression-discontinuity (RD) design we describe below. The EDT program defined the GPA threshold for each school using two measures. First, across *all* schools, a student could only be program-eligible if their GPA, which is defined on a scale from 1 to 7, was at least 5.3. This GPA requirement is based on the high-school GPA associated with the average university entrance-exam score in Chile. Second, program-eligible students had to perform in the top 30 percent of their school's cohort. Given the varied GPA distributions across the participating high schools, these two requirements created variation across schools in the share of each school's cohort that was program-eligible (i.e., from the top 2 percent to the top 30 percent). These school-specific eligibility criteria may improve the external validity of the inferences based on the RD design used in this study. That is, while the program intentionally focuses on higher-achieving students (i.e., those with higher GPAs), the variation in school-specific GPA thresholds (and, possibly, grading standards) implies the RD inferences do not rely exclusively on inferences around a single threshold.

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[6] Partner schools were identified for participation by selecting those vocational high schools where students performed comparatively well on 10^{th} grade assessments. However, these vocational schools underperformed relative to the average non-vocational public school. We exclude one partner high school from our study because it used teacher discretion to identify participating students rather than the student-assignment rule that we describe here and leverage in our regression-discontinuity (RD) design.

We also note that program take-up among eligible students was incomplete. Specifically, 33 of the 111 students for whom ITT=1 actually entered the EDT program while no program-ineligible students (ITT = 0) did so. This "fuzziness" in program take-up among eligible students reflected both declinations and students for whom contact information was faulty. We also note that the observed traits of program-eligible students who self-select to enter the program did not differ from those who did not participate. Nonetheless, we return to this issue in our analysis when, using a recent insight from Bertanha and Imbens (2019), we consider whether the program has heterogeneous effects across "compliers" and "never takers" as suggested by the Local Average Treatment Effect (LATE) Theorem.

3. Data

In this study, we examine the impact of the EDT program on three stages of students' academic progress: (1) the academic performance of students in high school; (2) the decision of students as to whether or not to take university entrance exams and their resulting scores on those exams; and (3) the matriculation rates of students in different institutions of higher education. We use detailed student-level administrative data provided by the national Ministry of Education to measure varied outcomes linked to these pivotal stages of students' academic trajectories as well as to identify baseline covariates that are also likely to influence student success.

Table 1 presents descriptive statistics on the different variables used in our study. The baseline covariate traits are gender, year of birth, and academic scores on a national standardized test in mathematics and language arts taken in 10th grade.[7] The proportion of females in the sample is 42 percent. By the end of 10th grade, over 70 percent of students were 15-16 years old. Their average score on the national standardized test taken in 10th grade is 0.3 standard deviations *below* the national average, both in language arts and mathematics, which reflects some negative selection into vocational high schools.

At the high school level, we focus on four distinct outcomes (Table 1). One is whether the student graduated on time from high school. And, among those who do complete high

[7] The *Sistema de Medición de la Calidad de la Educación* (Education Quality Measurement System, SIMCE) tests assess knowledge of the minimum content standards established in the national curriculum for different subjects. This examination is mandatory for all students, in certain grades, every two years.

school, we measure their GPA in 11th and 12th grades, both overall and specific to math and language-arts subjects. We find that 82 percent of the ITT sample completed high school on time. Among these high-school completers, the GPA measures were above 5 on a 7-point scale. This GPA places these students slightly below the average typical of college matriculants in Chile. Our outcome measures relevant to college transitions focus on taking standardized exams and, conditional on taking an exam, student performance. The means in Table 1 indicate that just over 60 percent of the ITT sample took the mandatory entrance exams in math and language-arts.[8] Nearly 58 percent of these students took an entrance exam specific to either history or science. Among these test takers, the performance of these students was roughly 30 to 40 percent of a standard deviation *below* the national averages (Table 1).

Our third set of outcome measures captures students' matriculation into higher education during the 4-year period after their on-time high-school graduation (i.e., 2015 through 2018; Table 1). Specifically, we separately measure matriculation at the four distinct types of post-secondary institutions described in the prior section: a CRUCH university, a private non-CRUCH university, a professional learning institute, and a technical training center. The CRUCH universities are generally, though not always, more selective. They are also as more affordable for the lower-income students who attended vocational high schools. Therefore, if the EDT program is effective, we would particularly expect it to increase the probability of attending a CRUCH university. Similarly, we also measure matriculation in Chile's top two universities (Universidad de Chile and Pontificia Universidad Católica de Chile), which are uniquely selective CRUCH members. However, we also measure matriculation at non-CRUCH universities, some of which have open-admissions policies and do not require the PSU entrance exams. Similarly, we also measure matriculation at professional learning institutes and technical training centers, which offer programs that culminate in non-academic degrees. These measures allow us to examine whether the EDT program redirected students from professional and vocational postsecondary training to universities. Notably, the means in Table 1 indicate that only 8 percent of the ITT sample entered a CRUCH university in this 4-year window. And only 3 percent of the sample

[8] To place this in perspective, we note that 71 percent of public high school graduates took the PSU. The corresponding rates from private-subsidized and private high schools are 87 percent and 98 percent, respectively.

matriculated at one of Chile's top two universities. These low rates of matriculation underscore the challenges vocational high-school students face in gaining admission to selective universities. In contrast, nearly twice as many students (i.e., 15 percent) entered a private, non-CRUCH university. This pattern could be due to the barriers of taking and performing sufficiently well on the entrance exams required by CRUCH universities. Furthermore, 38 percent entered a professional learning institute while 15 percent attended a technical training center. Overall, 68 percent of the ITT sample had at least some form of postsecondary enrollment.[9]

4. **Regression discontinuity design**

The research design used in this study identifies the impact of the EDT program by effectively comparing those students who just met the eligibility requirement for assignment to the EDT program (i.e., a cumulative GPA in 9th and 10th grade above the school-specific cutoff score) to those who were ineligible. Stated differently, this regression discontinuity (RD) design examines whether student outcomes "jump" at the threshold that defines eligibility. The RD design is implemented by estimating reduced-form equations of the following general form:

$$Y_{is} = \beta_0 + \beta_1 I(GPA_{is} > 0) + f(GPA_{is}) + \Gamma X_{is} + \lambda_s + \varepsilon_{is}$$

where Y_{is} is a student's *i* outcome, in school *s*. The variable GPA_{is} is the assignment variable (i.e., the cumulative GPA in 9th and 10th grade, centered at the relevant cutoff score). The parameter of interest, β_1, identifies the jump in outcomes when the forcing variable is above the cutoff (i.e., ITT = 1), conditional on the smooth function of the assignment variable, $f(GPA_{is})$. In the regressions, we specify $f(GPA_{is})$ as linear but allow for differential slopes above and below the threshold. The variable, X_{is}, refers to student-level controls, and λ_s refers to school fixed effects.

This research design relies on several key assumptions that we examine. First, we assess whether there is a discrete increase in the probability of EDT participation at the threshold that defines a student's eligibility. Table 2 reports the key results from these first-stage regressions. Across different specifications, we find robust evidence that the likelihood of

[9] The sum of the matriculation rates at these four types of institutions exceeds this rate because some students attended more than 1 type of institution during our 4-year longitudinal window.

participating in the program increases by roughly 36 percentage points at the threshold. Appendix Table A2 also shows that this first-stage effect appears quite robust across specifications based on data in increasingly tight bandwidths around the eligibility threshold. We also illustrate this graphically in Figure 1 which shows students' treatment statuses as a function of the assignment variable (i.e., cumulative GPA in 9th and 10th grades). This figure organizes the data bins of width 0.2 defined by the assignment variable. The figure also illustrates the partial compliance with the ITT implied by the eligibility criteria for students above the GPA threshold. About 30 percent of the students with a GPA above the threshold participated in the program (i.e., compliers among those for whom ITT = 1). In our analysis, we consider the treatment heterogeneity in program impact that may exist across compliers and never-takers (Bertanha and Imbens 2019). Figure 1 also illustrates that no students below the eligibility threshold (i.e., ITT = 0) participated in the program.

A second broad assumption of RD designs like ours is that a student's position relative to the GPA threshold that determined program eligibility is conditionally random. One approach to examining this assumption is to consider density tests (e.g., McCrary 2008) that explore the manipulability of the assignment variable by asking if the distribution of observations appears smooth through the ITT threshold. The graphs in Figure 2 illustrate such evidence. The first panel shows a frequency histogram of observations. This figure suggests a slight increase in the number of observations to the right of the threshold. However, the second panel illustrates the density test first suggested by McCrary (2008). Using this approach, we fail to reject the null hypothesis that the distribution is smooth through the ITT threshold. We also implemented the density test proposed by Cattaneo, Jansson, and Ma (2018) and similarly fail to reject the null hypothesis that the distribution of observations is continuous through the threshold. These results are consistent with the maintained assumption that the baseline GPA variable was not systematically manipulated to change program eligibility.

A related assumption is that students' potential outcomes are continuous through the threshold. We provide evidence on this assumption by examining the balance of baseline student traits around the ITT threshold. Specifically, we estimated auxiliary RD regressions where these baseline traits are the dependent variables. The key results from these regressions are reported in Table A1. These results consistently indicate that program eligibility had small and statistically insignificant effects on these baseline measures. This evidence of covariate balanced around the ITT threshold is consistent with the causal warrant of the RD design. In the results we present below, we also explore the robustness of our estimates to the choice of functional form. Specifically, we examine the robustness of our findings to local linear regressions based on discontinuity samples based on observations that are in increasingly tight bandwidths around the ITT threshold. We also report the results of estimates based on the algorithmic choice of bandwidths and the estimate approaches recommend by Imbens and Kalyaranaman (2012) and Calonico et al. (2020). Finally, as ad-hoc evidence on the robustness of our results, we also report the effects associated with "placebo" thresholds that were not relevant to program eligibility.

5. Results

In Table 3, we present RD estimates of the impact of EDT program eligibility on 4 different high-school outcomes and across specifications that introduce student covariates and school fixed effects as control variables. These results consistently indicate that EDT eligibility had small and statistically insignificant effects on the probability of graduating from high school. We also find that, among high-school graduates, the estimated impact of EDT eligibility on *overall* GPA was consistently positive but statistically insignificant. In contrast, the remaining estimates in Table 3 suggest that EDT eligibility led to particularly large and statistically significant increases in math GPA (i.e., 0.42 on a 7-point scale). This estimate amounts to an 8.3 percent increase relative to the sample mean (i.e., 5.031).[10] The estimated effects of EDT eligibility on language-arts GPA in 11th and 12th grades are also statistically significant but smaller (i.e., 4 to 5 percent of the sample mean).[11] Figure 3 provides visual illustrations of these estimated effects and clearly suggest discrete increases in these GPA measures at the eligibility threshold, particularly for math. In Appendix Table A2, we explore the robustness of these results to alternative approaches to functional form. Specifically, we

[10] Though GPA is on a 7-point scale, a 4.0 or higher is required to pass a course. Because the variance in the GPA measures is correspondingly quite small, this reduced-form estimate also corresponds to an effect size of 0.53 (i.e., 0.42/0.793). Furthermore, given the first-stage estimate of 0.36, these results imply that the estimated effect of *participating* in the EDT program is to increase math GPA by 23 percent.

[11] The curricula in these high schools has a rigid structure so these do not reflect any change in courses taken. Also, large gains in math and language arts along with no detectable gains in overall GPA are possible because students typically take around 11 subjects in an academic year.

report local linear regressions based on increasingly tight bandwidths of data close to the threshold. We also report estimates based on triangular kernel weights and optimal bandwidths (Imbens and Kalyanaraman 2012, Calonico et al. 2020). These results suggest that the estimated impact of EDT eligibility on language-arts GPA, while still positive, becomes smaller and statistically insignificant in these specifications. In contrast, the estimated impact of EDT eligibility on math GPA is generally robust across these varying approaches.

Table 4 presents the estimated effects of EDT eligibility on the probability of taking university entrance exams and scores on those exams. In general, we find no clear evidence that the EDT program increased the likelihood of taking the core math/language-arts exam required for university admissions or the subject exams in the social or natural sciences required for admission to specific majors. However, among those taking the exam, the estimated effects of EDT eligibility are large and positive in all four subjects (i.e., math, language arts, social sciences, and science). Figure 4 provides a visual illustration of these estimates. The results in Table 4 indicate that these estimates are only statistically significant in the case of math and science. The entrance-exam gains attributable to EDT eligibility are notably large. For example, the math gain (i.e., 0.283) is nearly equivalent to the gap between the vocational high-school students and test-takers nationally (i.e., -0.319, Table 1). However, it should also be noted that these point estimates generally remain similarly large, though not always statistically significant, in specifications based on tighter bandwidths of the data and kernel-weighted approaches (Appendix Table A3).

We next turn to estimates of how EDT eligibility influenced different margins of matriculation in post-secondary education. The RD estimates presented in Table 5 suggest that the EDT program reduced the likelihood of post-secondary attendance at a technical training center, a professional learning institute, and a private non-CRUCH university. In contrast, EDT eligibility increased the likelihood of attending a selective CRUCH university. In particular, these gains were largely concentrated among Chile's two most selective universities. The reduction in the probability of attending a technical training center is particularly large and statistically significant as are the gains in the probability of matriculating at a highly selective university. Figure 5 illustrates these effects visually as well as underscores the magnitude of these estimated effects. For example, to the left of the eligibility threshold (i.e., ITT = 0), roughly 20 percent of students attended a technical training center after high school. However, this matriculation rate falls by roughly 10 percentage points to the right of the threshold (i.e., ITT = 1). Similarly, the probability of attending one of Chile's two most selective universities is only about 5 percent to the left of the threshold but jumps to about 20 percent to the right. The treatment-on-the-treated (TOT) estimates implied by these results is quite large. For example, these RD results suggest that participation in the EDT program increased the likelihood of attending a highly selective university by 38.8 percentage points (i.e., 0.140/0.361). Appendix Table A4 shows that these estimates are of generally similar magnitude but lose significance when using restricted bandwidths of data.

We also explored the treatment heterogeneity in these results in two ways. First, we examined our reduced-form estimates in sub-samples defined by gender and by dimensions of baseline academic achievement (i.e., 10^{th} grade SIMCE scores). The key results of this approach are reported in Appendix Table A6. Notably, these estimates suggest that the EDT program was particularly effective in increasing the probability that boys attended one of the two elite universities. We also see strong evidence that the gains in math performance in high school and on entrance exams as well as the likelihood of attending an elite university were highly concentrated among students who had above-average math performance on the 10^{th} grade exam. This heterogeneity underscores the role of the EDT program in supporting academically promising students who, for whatever reason, found themselves attending a vocational high school. Because the treatment compliance with the ITT is not perfect, the LATE Theorem implies another potential form of treatment heterogeneity. That is, in our context, these results may only identify the causal impact of the EDT program for students who complied with their ITT. We explore this using an approach suggested by Bertanha and Imbens (2019). Specifically, we estimated our reduced-form RD specifications using only observations from students who did not participate in the program (i.e., EDT = 0). This auxiliary RD framework effectively compares compliers and never-takers (i.e., to the left of the threshold where ITT = 0) to never-takers (i.e., to the right of the threshold where ITT = 1). We report the RD results from this approach in Appendix Table A7 for our key outcomes. The results generally suggest that, among this sample of students who did **not** participate in the EDT program, never-takers had better academic outcomes. For example, their mathematics GPA in grades 11 and 12 was significantly higher than among never-takers and compliers. These results suggest that the effects we estimate for compliers may not generalize to other sub-populations. For example, never-takers who have comparatively high academic outcomes may have perceived that they were less likely to gain further from the program and chose not to enter regardless of their ITT.

6. Conclusion

Thoughtfully designed high-school programs that support the development of vocational skills appear to play an important, and perhaps underutilized, role in fostering the long-run integration of students into gainful employment. This important evidence has motivated recommendations for broader investments in vocational opportunities in high schools. However, the expansion of vocational education could also have unintended, negative consequences for academically capable, low-income students. Recent evidence suggests that these "missing one-offs" tend to mimic the post-secondary educational choices made by their peers with weaker academic qualifications (Avery and Hoxby, 2013). It follows that expanded vocational programs may exacerbate inequality by increasing the sorting of high-performing students away from the selective university admissions for which they may be qualified. This study provides novel empirical evidence that is broadly consistent with this concern. Specifically, the RD evidence presented here indicates that supporting the college readiness of high-performing, low-income vocational students (i.e., the EDT program) meaningfully improves their high-school academic performance (i.e., at least in math), their ability to meet the rigid requirements for admission to elite universities, and, ultimately, their decision to matriculate at such institutions. These findings underscore the serious educational under-investments that can occur for such students when institutional design guides them towards vocationally focused programs of study. These results also constitute an important proof of concept. That is, our findings indicate the promising impact of programs seeking to support academically capable vocational students. This evidence of impact suggests that other similarly motivated and targeted programs, possibly with very different design features, merit consideration.

However, apart from the evidence of impact, there are also several other issues to consider with regard to the implications of these findings. One is the EDT program as currently constituted has a non-trivial operating cost (i.e., roughly $3,200 per student over the two-year span of the program). One compelling way to put this into some perspective is to compare the cost-effectiveness of the EDT program to other initiatives with firm evidence of efficacy. For example, an intervention report from the U.S. Department of Education (What Works Clearinghouse, 2018) notes that summer counseling costs no more than $200 per student and has mixed evidence of effectiveness in increasing college enrollment (i.e., by an average of 5 percentage points). However, these programs generally target reducing "summer melt" among students with a clear intention of going to college. Therefore, the relevance of such light-touch programs for efforts to support the "missing one-offs" in vocational schools is at best uncertain. The recent evidence from "dual enrollment" programs that allow high school students to take some college courses and earn college credits is more clearly comparable. A recent intervention report (What Works Clearinghouse, 2017) indicates that, like the EDT program, such programs generate substantial gains in college access (i.e., an average of 15 percentage points). The report also notes that the costs of such programs are uncertain. However, because dual-enrollment programs also involve seat time in classes on university campuses, it seems reasonable to suppose that its costs are likely to be broadly similar to those of the EDT program.

A second important and related caveat is that the EDT program studied here operated on a fairly small scale (i.e., serving students from 8 high schools at one university site). On the one hand, operating the program at a larger scale could conceivably generate meaningful savings through the realization of economies of scale. However, whether the program could be scaled or replicated elsewhere with reasonable fidelity and have similar impact should be viewed as an open empirical question. A third and final consideration involves longer-run effects. Our finding that the EDT program can promote the matriculation of "missing one-offs" at elite universities is important given the evidence of high returns to attending such institutions (Hastings, Neilson and Zimmerman, 2013). However, the social-welfare implications of the EDT program will ultimately depend on how it influences persistence and completion at such universities as well as longer-run economic success. Because the program is so recent, it is not yet possible to examine those outcomes for its earliest cohorts. However, that will also be an important area for further research along with the evaluation of other promising strategies to support the educational potential and ambition of these students.

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Figure 1. EDT program participation

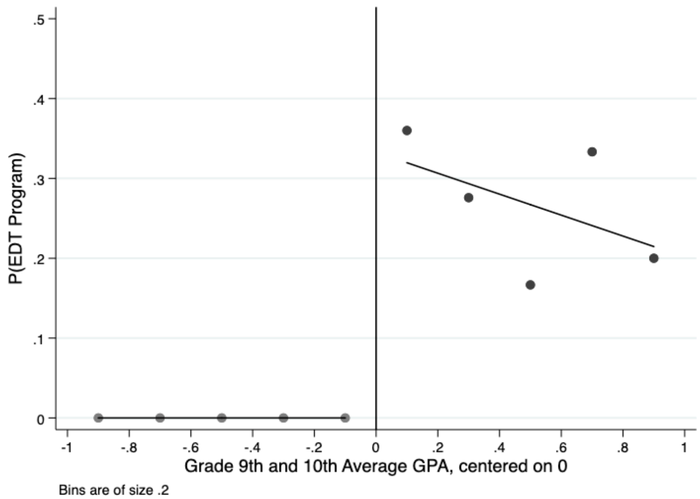
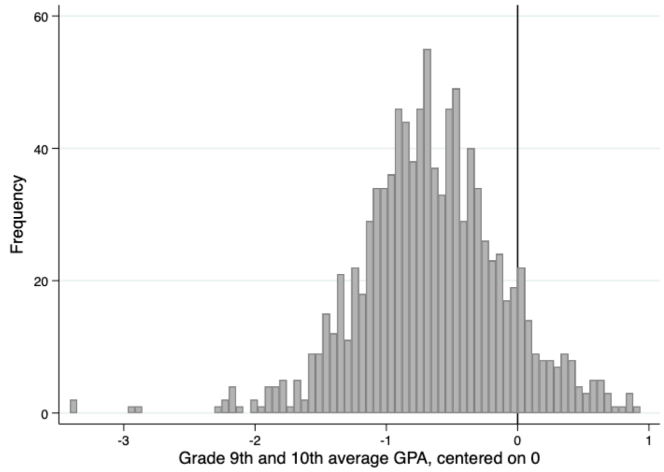
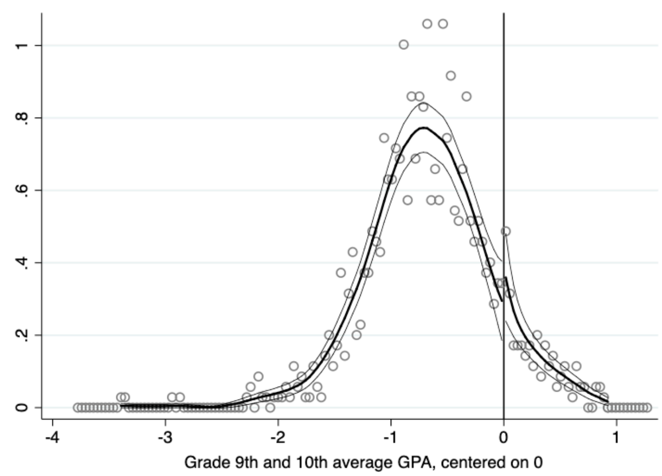


Figure 2. Distribution of baseline GPA

(a) Frequency histogram



(b) Density Test (McCrary, 2008)



(a) Density test (Cattaneo, Jansson, and Ma, 2018)

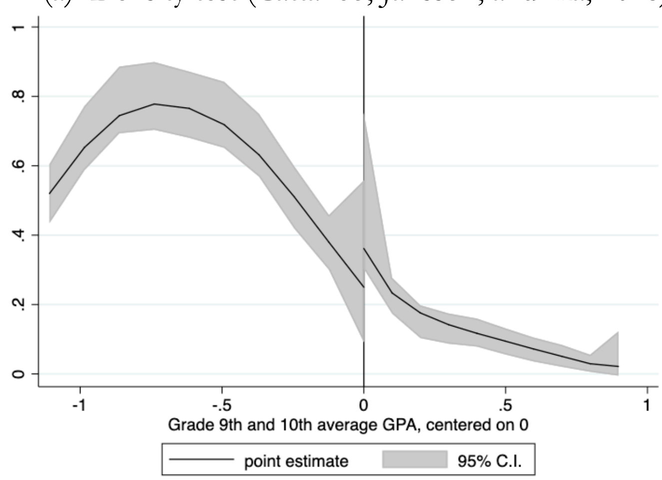
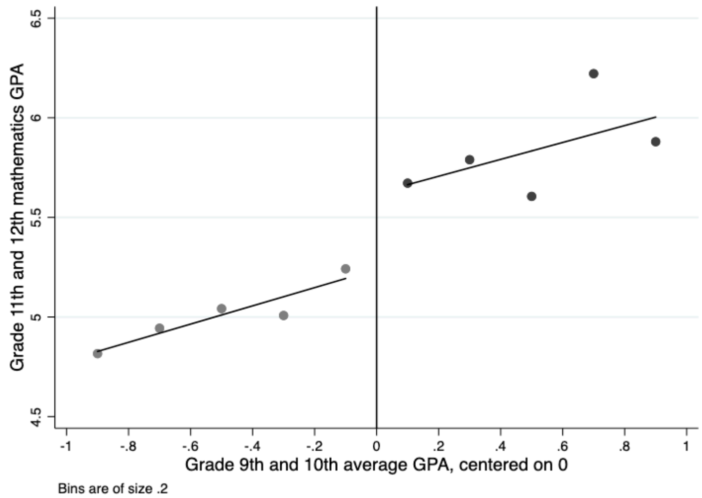


Figure 3. High school performance

(a) Grade 11th-12th mathematics GPA



(b) Grade 11th-12th Language arts GPA

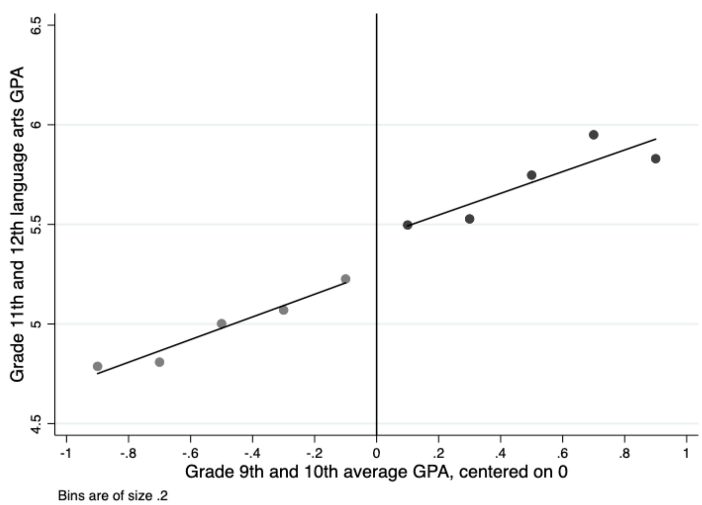
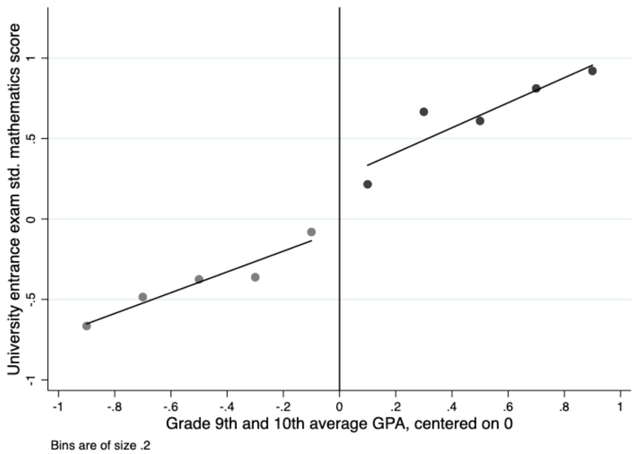
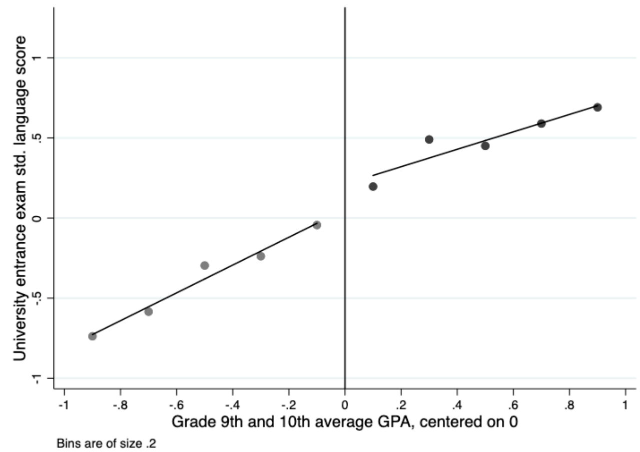


Figure 4. University entrance exam performance

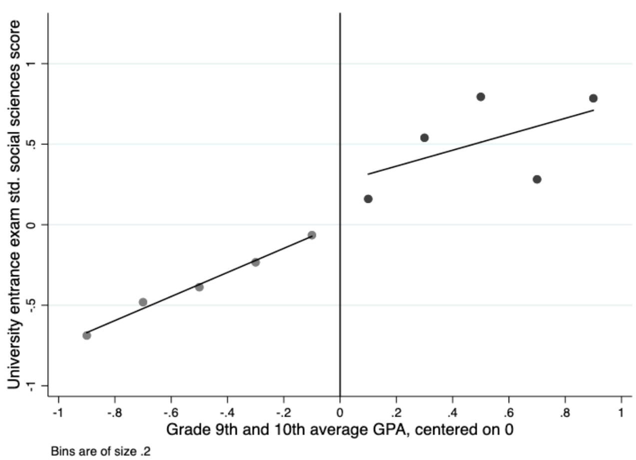
(a) Standardized mathematics score



(b) Standardized language arts score



(c) Standardized social sciences score



(d) Standardized science score

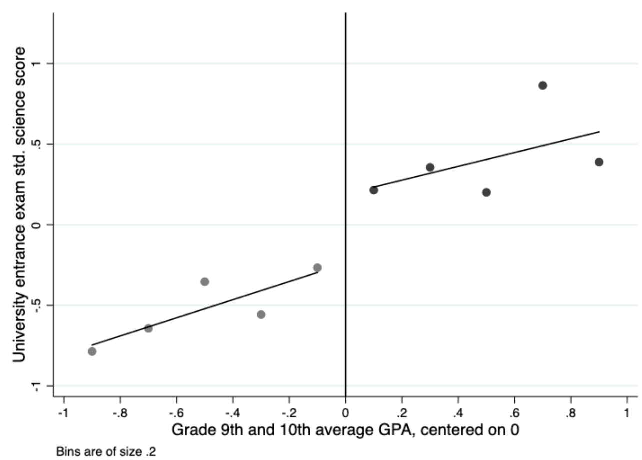
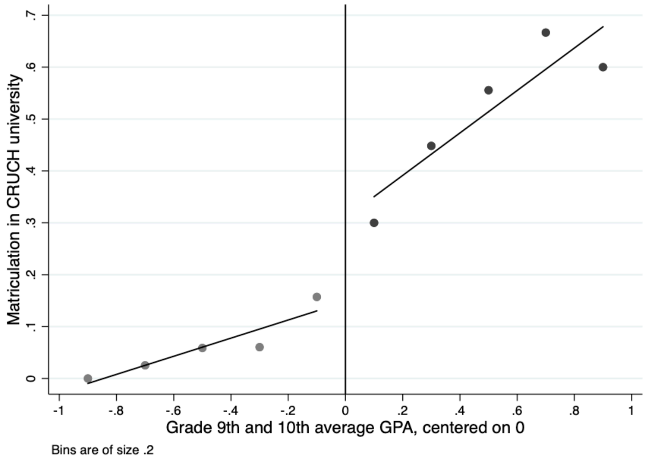
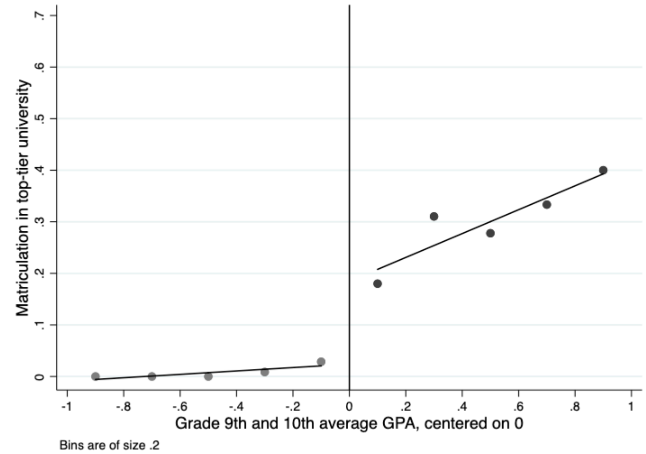


Figure 5. Matriculation in higher education institutions

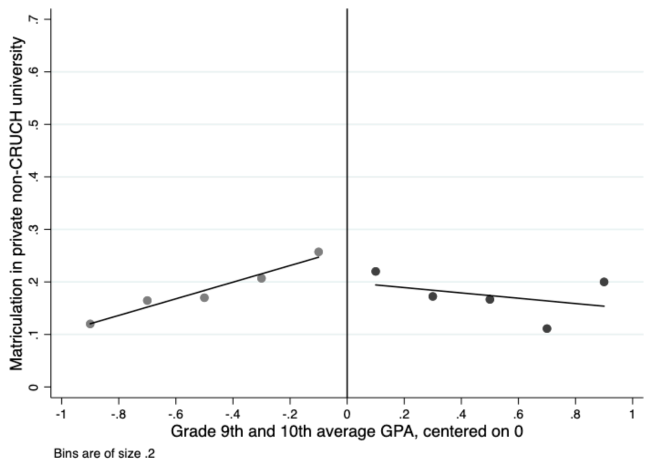
(a) CRUCH university



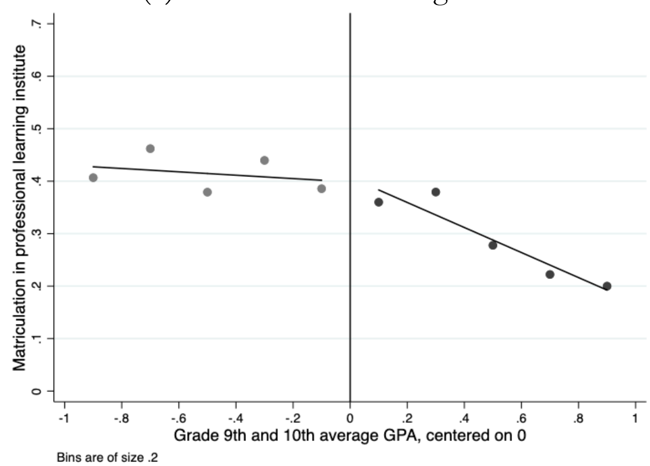
(b) Top-tier, highly-selective university



(c) Private non-CRUCH university



(d) Professional learning institute



(e) Technical training center

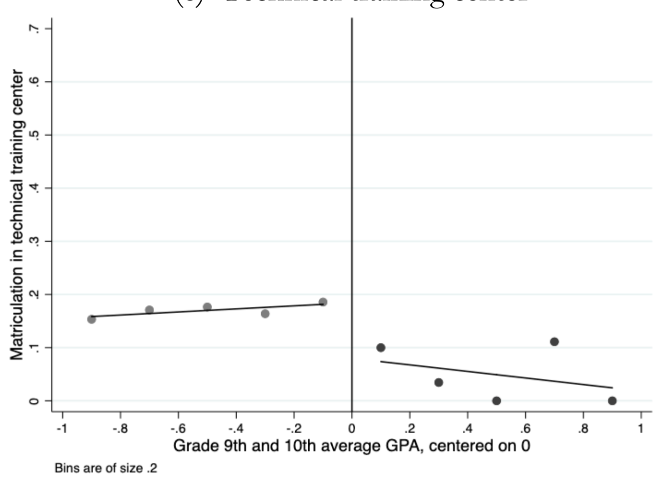


Table 1. Summary statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Grade 9-10 avg. GPA	1003	5.113	0.526	2.485	6.692
Grade 9-10 avg. GPA centered	1003	-0.660	0.551	-3.390	0.898
I[Grade 9-10 avg. GPA centered >0]	1003	0.111	0.314	0	1
EDT participation	1003	0.033	0.178	0	1
Baseline students' traits					
Female	1003	0.418	0.493	0	1
Year of birth	1003	1995.9	0.815	1992	1997
Year of birth 1995	1003	0.193	0.395	0	1
Year of birth 1996	1003	0.512	0.500	0	1
Year of birth 1997	1003	0.243	0.429	0	1
10th grade language arts test (SIMCE)	1003	242.3	49.0	130.6	375.0
10th grade mathematics test (SIMCE)	1003	247.3	47.3	122.5	392.9
High School					
High school graduation	1003	0.815	0.389	0	1
Avg. GPA, 11-12th grade [1.0-7.0 scale]	817	5.382	0.478	3.948	6.896
Mathematics GPA, 11-12th grade [1.0-7.0 scale]	817	5.031	0.793	2.950	6.950
Language arts GPA, 11-12th grade [1.0-7.0 scale]	817	5.010	0.619	3.350	6.950
College entrance exam					
Probability of taking mandatory tests (math and language arts)	1003	0.605	0.489	0	1
Probability of taking specific tests (history or science)	1003	0.578	0.494	0	1
Probability of taking history specific test	1003	0.354	0.478	0	1
Probability of taking science specific test	1003	0.314	0.464	0	1
Std. mathematics test score	608	-0.319	0.831	-3.000	2.155
Std. language arts test score	612	-0.319	0.796	-2.673	2.082
Std. social sciences test score	356	-0.302	0.849	-2.691	1.918
Std. science test score	320	-0.425	0.797	-3.045	1.491
Matriculation in higher education institutions (2015-2018)					
CRUCH university	1,003	0.08	0.270	0	1
Top-tier, highly-selective university	1,003	0.03	0.173	0	1
Private non-CRUCH university	1,003	0.15	0.359	0	1
Professional learning institute	1,003	0.38	0.486	0	1
Technical training center	1,003	0.15	0.358	0	1

Table 2. First stage RD estimates, EDT program participation

Treatment	(1)	(2)	(3)
I [9-10th grade GPA>0]	0.361***	0.362***	0.364***
	(0.070)	(0.070)	(0.069)
Observations	1,003	1,003	1,003
R-squared	0.283	0.285	0.302
AIC	-942	-928	-940
Students controls	No	Yes	Yes
School fixed effects	No	No	Yes

Note: All models condition on grade 9-10th avg. GPA with separate linear splines above and below the threshold. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3. Reduced-form RD estimates: High school outcomes

	(1)	(2)	(3)	Obs.
High school graduation	-0.026 (0.025)	-0.029 (0.026)	-0.045 (0.034)	1,003
Grade 11th-12th avg. GPA | HS graduation				
Overall GPA	0.088 (0.086)	0.079 (0.080)	0.073 (0.058)	817
Mathematics	0.423*** (0.149)	0.421*** (0.136)	0.413*** (0.111)	817
Language arts	0.280*** (0.106)	0.250** (0.097)	0.207** (0.080)	817
Students controls	No	Yes	Yes	
School fixed effects	No	No	Yes	

Note: Each point estimate is from a separate regression where each high school outcome is the dependent variable. All models condition on grade 9-10th avg. GPA with separate linear splines above and below the threshold. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 4. Reduced-form RD estimates: University entrance exam scores

	(1)	(2)	(3)	Obs.
Probability of taking the university entrance exam				
Mathematics and language arts	0.038 (0.055)	0.029 (0.053)	0.006 (0.056)	1,003
Subject tests	0.024 (0.061)	0.015 (0.059)	-0.007 (0.059)	1,003
Social Sciences	0.090 (0.080)	0.084 (0.080)	0.084 (0.081)	1,003
Science	-0.085 (0.078)	-0.091 (0.078)	-0.125* (0.074)	1,003
University entrance exam standardized scores				
Mathematics	0.283** (0.138)	0.295** (0.115)	0.225* (0.117)	608
Language arts	0.199 (0.128)	0.180* (0.105)	0.167 (0.105)	612
Social Sciences	0.185 (0.173)	0.180 (0.150)	0.160 (0.144)	356
Science	0.472*** (0.171)	0.362** (0.163)	0.324* (0.174)	320
Student controls	No	Yes	Yes	
School fixed effects	No	No	Yes	

Note: Each point estimate is from a separate regression where each university entrance exam variable is the dependent variable. All models condition on grade 9-10th avg. GPA with separate linear splines above and below the threshold. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 5. Reduced-form RD estimates: Matriculation in higher education institutions

	(1)	(2)	(3)	Obs.
CRUCH university	0.148**	0.137**	0.125*	1,003
	(0.068)	(0.065)	(0.064)	
Top-tier, highly-selective university	0.140**	0.135**	0.127**	1,003
	(0.058)	(0.056)	(0.055)	
Private non-CRUCH university	-0.012	-0.020	-0.017	1,003
	(0.066)	(0.066)	(0.067)	
Professional learning institute	-0.052	-0.047	-0.057	1,003
	(0.078)	(0.079)	(0.080)	
Technical training center	-0.102**	-0.097**	-0.093*	1,003
	(0.047)	(0.047)	(0.048)	
Student controls	No	Yes	Yes	
School fixed effects	No	No	Yes	

Note: Each point estimate is from a separate regression where each outcome variable is the dependent variable. All models condition on grade 9-10th avg. GPA with separate linear splines above and below the threshold. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

A1. Auxiliary RD estimates: Baseline covariate balance

Dependent variable	Estimate
Female	0.069
	(0.079)
Grade 10th language arts test (SIMCE)	3.906
	(5.789)
Grade 10th mathematics test (SIMCE)	2.676
	(6.181)
Year of birth 1995	0.011
	(0.024)
Year of birth 1996	-0.010
	(0.026)
Year of birth 1997	-0.040
	(0.026)

Note: Each point estimate is from a separate regression where the baseline covariate is the dependent variable. All models condition on school fixed effects, grade 9-10th avg. GPA with separate linear splines above and below the threshold, and student controls. N=1,003 in all models. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

A2. RD estimates by bandwidth restrictions: EDT participation and high school outcomes

Dependent variable:	EDT program participation		High school graduation		Grade 11th-12th GPA, conditional on HS graduation					
					Overall GPA		Mathematics		Language arts	
Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Estimate	N	*Estimate*	N	*Estimate*	N	*Estimate*	N	*Estimate*	N
Full sample	0.361*** (0.070)	1,003	-0.026 (0.025)	1,003	0.088 (0.086)	817	0.423*** (0.149)	817	0.280*** (0.106)	817
|9-10th grade GPA| ≤ 1.0	0.361*** (0.070)	758	0.072** (0.028)	758	0.037 (0.090)	679	0.392** (0.155)	679	0.150 (0.111)	679
|9-10th grade GPA| ≤ 0.9	0.361*** (0.070)	689	0.075** (0.029)	689	0.041 (0.091)	622	0.384** (0.157)	622	0.141 (0.113)	622
|9-10th grade GPA| ≤ 0.8	0.364*** (0.074)	603	0.070** (0.034)	603	0.038 (0.096)	545	0.390** (0.163)	545	0.098 (0.119)	545
|9-10th grade GPA| ≤ 0.7	0.375*** (0.075)	521	0.091** (0.036)	521	0.032 (0.100)	478	0.370** (0.169)	478	0.092 (0.124)	478
|9-10th grade GPA| ≤ 0.6	0.391*** (0.077)	436	0.021 (0.034)	436	0.022 (0.108)	400	0.403** (0.182)	400	0.116 (0.133)	400
|9-10th grade GPA| ≤ 0.5	0.361*** (0.085)	354	0.028 (0.036)	354	0.002 (0.115)	329	0.339* (0.196)	329	0.133 (0.142)	329
Kernel weights	0.396*** (0.088)	401	0.043 (0.036)	401	-0.028 (0.119)	374	0.307 (0.203)	374	0.122 (0.147)	374
CCFT Estimates	0.446*** (0.104)	179	0.034 (0.061)	145	-0.096 (0.128)	235	0.289 (0.254)	162	0.126 (0.191)	154
IK Estimates	-		-		0.000 (0.112)	351	0.403** (0.179)	414	0.085 (0.125)	461

Note: Each point estimate is from a separate regression where the outcome variable is the dependent variable. Each cell contains a regression of the outcome variable for individuals within the specified bandwidth on I[9-10th grade GPA≥ 0] and a linear spline of the assignment variable. Columns 2, 4, 6, 8, and 10 contain the number of individuals in the bandwidth. Kernel weights estimate triangular kernel weights for observations within one standard deviation of the forcing variable. CCF are Calonico, Cattaneo, and Farrell (2018) suggested bandwidths with kernel weights. IK are Imbens and Kalyanaraman (2012) suggested bandwidths with kernel weights. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

A3. RD estimates by bandwidth restrictions: University entrance exam scores

Dependent variable:	University entrance exam standardized scores							
	Mathematics		Language arts		Social Sciences		Science	
Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Estimate	N	*Estimate*	N	*Estimate*	N	*Estimate*	N
Full sample	0.283** (0.138)	608	0.199 (0.128)	612	0.185 (0.173)	356	0.472*** (0.171)	320
|9-10th grade GPA| ≤ 1.0	0.268* (0.145)	544	0.109 (0.137)	547	0.149 (0.186)	319	0.438** (0.186)	288
|9-10th grade GPA| ≤ 0.9	0.251* (0.148)	504	0.088 (0.140)	507	0.091 (0.191)	293	0.458** (0.191)	273
|9-10th grade GPA| ≤ 0.8	0.269* (0.156)	447	0.099 (0.148)	449	0.123 (0.207)	261	0.472** (0.216)	238
|9-10th grade GPA| ≤ 0.7	0.234 (0.162)	398	0.134 (0.156)	400	0.070 (0.215)	234	0.426* (0.233)	212
|9-10th grade GPA| ≤ 0.6	0.222 (0.173)	339	0.145 (0.169)	340	-0.006 (0.232)	198	0.593** (0.250)	186
|9-10th grade GPA| ≤ 0.5	0.086 (0.185)	282	0.079 (0.178)	283	0.100 (0.245)	169	0.359 (0.263)	152
Kernel weights	0.072 (0.184)	318	0.060 (0.187)	319	0.053 (0.258)	186	0.268 (0.281)	174
CCFT Estimates	0.102 (0.234)	131	0.102 (0.223)	165	0.081 (0.336)	83	0.175 (0.392)	66
IK Estimates	0.241 (0.163)	388	0.104 (0.151)	424	0.024 (0.227)	211	0.597** (0.253)	182

Note: Each point estimate is from a separate regression where the outcome variable is the dependent variable. Each cell contains a regression of the outcome variable for individuals within the specified bandwidth on I[9-10th grade GPA≥ 0] and a linear spline of the assignment variable. Columns 2, 4, 6, 8, 10, 12, 14, and 16 contain the number of individuals in the bandwidth. Kernel weights estimate triangular kernel weights for observations within one standard deviation of the forcing variable. CCF are Calonico, Cattaneo, and Farrell (2018) suggested bandwidths with kernel weights. IK are Imbens and Kalyanaraman (2012) suggested bandwidths with kernel weights. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

A4. RD estimates by bandwidth restrictions: Matriculation in higher education institutions

Dependent variable:	CRUCH university		Top-tier, highly-selective university		Non-CRUCH private university		Professional learning institute		Technical training centers	
Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Estimate	N	*Estimate*	N	*Estimate*	N	*Estimate*	N	*Estimate*	N
Full sample	0.148** (0.068)	1,003	0.140** (0.058)	1,003	-0.012 (0.066)	1,003	-0.052 (0.078)	1,003	-0.102** (0.047)	1,003
|9-10th grade GPA| ≤ 1.0	0.102 (0.072)	758	0.130** (0.059)	758	-0.024 (0.072)	758	0.007 (0.085)	758	-0.092* (0.053)	758
|9-10th grade GPA| ≤ 0.9	0.097 (0.073)	689	0.128** (0.059)	689	-0.013 (0.074)	689	0.013 (0.086)	689	-0.089 (0.054)	689
|9-10th grade GPA| ≤ 0.8	0.069 (0.075)	603	0.116* (0.061)	603	-0.002 (0.078)	603	0.028 (0.091)	603	-0.085 (0.059)	603
|9-10th grade GPA| ≤ 0.7	0.069 (0.079)	521	0.134** (0.061)	521	-0.031 (0.081)	521	0.018 (0.095)	521	-0.068 (0.063)	521
|9-10th grade GPA| ≤ 0.6	0.042 (0.084)	436	0.095 (0.065)	436	-0.024 (0.088)	436	-0.011 (0.101)	436	-0.048 (0.066)	436
|9-10th grade GPA| ≤ 0.5	-0.003 (0.089)	354	0.064 (0.069)	354	0.001 (0.094)	354	0.057 (0.108)	354	-0.080 (0.071)	354
Kernel weights	-0.021 (0.092)	401	0.069 (0.070)	401	0.004 (0.100)	401	0.057 (0.112)	401	-0.096 (0.073)	401
CCFT Estimates	-0.059 (0.127)	145	0.099 (0.086)	162	-0.017 (0.117)	203	0.039 (0.125)	239	-0.134 (0.098)	160
IK Estimates	0.010 (0.093)	316	0.095 (0.066)	425	-0.029 (0.089)	413	0.001 (0.085)	764	-0.105** (0.052)	817

Note: Each point estimate is from a separate regression where the outcome variable is the dependent variable. Each cell contains a regression of the outcome variable for individuals within the specified bandwidth on I[9-10th grade GPA≥ 0] and a linear spline of the assignment variable. Columns 2, 4, 6, 8, and 10 contain the number of individuals in the bandwidth. Kernel weights estimate triangular kernel weights for observations within one standard deviation of the forcing variable. CCFT are Calonico, Cattaneo, Farrell and Titiunik (2017) suggested bandwidths with kernel weights. IK are Imbens and Kalyanaraman (2012) suggested bandwidths with kernel weights. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

A5. Placebo RD estimates

	EDT program participation	Grade 11-12th GPA (conditional on high school graduation) Mathematics	Language arts	University entrance exam standardized scores Mathematics	Science	Matriculation in higher education CRUCH university	Top-tier, highly-selective university	Technical training center
I[Grade 9-10th avg. GPA > -1.0]	-0.005	-0.090	-0.036	-0.240*	-0.148	0.013	-0.003	0.041
	(0.004)	(0.090)	(0.074)	(0.133)	(0.173)	(0.014)	(0.006)	(0.042)
I[Grade 9-10th avg. GPA > -0.5]	-0.012**	-0.159*	-0.250***	-0.030	-0.027	-0.009	-0.011*	0.060
	(0.005)	(0.085)	(0.061)	(0.097)	(0.129)	(0.021)	(0.006)	(0.038)
I[Grade 9-10th avg. GPA >= 0]	0.347***	0.424***	0.235***	0.156	0.148	0.098	0.082	-0.082
	(0.079)	(0.122)	(0.090)	(0.134)	(0.195)	(0.071)	(0.060)	(0.052)
I[Grade 9-10th avg. GPA > 0.5]	0.089	0.058	-0.123	0.663**	0.911**	0.118	0.232	-0.069
	(0.167)	(0.242)	(0.170)	(0.272)	(0.367)	(0.184)	(0.176)	(0.063)
Observations	1,003	817	817	608	320	1,003	1,003	1,003
R-squared	0.304	0.376	0.449	0.45	0.405	0.303	0.277	0.025

Note: Each point estimate is from a separate regression. All models condition on school fixed effects, grade 9-10th avg. GPA with separate linear splines above and below the threshold, and student controls. Grade 9-10th average GPA is centered at zero. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

A6. Reduced-form RD estimates by subgroups

Dependent variable:			Grade 11-12th GPA (conditional on high school graduation)		University entrance exam standardized scores		Matriculation in higher education institutions		
Sample		EDT program participation	Mathematics	Language arts	Mathematics	Science	CRUCH university	Top-tier, highly-selective university	Technical training center
Full sample		0.364***	0.413***	0.207**	0.225*	0.324*	0.125*	0.127**	-0.093*
		(0.069)	(0.111)	(0.080)	(0.117)	(0.174)	(0.064)	(0.055)	(0.048)
	N	*1,003*	*817*	*817*	*608*	*320*	*1,003*	*1,003*	*1,003*
Female		0.465***	0.397**	0.175	0.250	0.422*	0.156*	0.066	-0.134**
		(0.093)	(0.155)	(0.107)	(0.175)	(0.242)	(0.086)	(0.067)	(0.067)
	N	*419*	*347*	*347*	*272*	*145*	*419*	*419*	*419*
Male		0.229**	0.411**	0.265**	0.120	0.115	0.114	0.206**	-0.051
		(0.097)	(0.161)	(0.124)	(0.150)	(0.261)	(0.097)	(0.090)	(0.072)
	N	*584*	*470*	*470*	*336*	*175*	*584*	*584*	584
Grade 10th language arts test		0.322***	0.375***	0.159*	0.279**	0.380*	0.137	0.160**	-0.084
≥ Sample mean		(0.075)	(0.124)	(0.090)	(0.133)	(0.193)	(0.083)	(0.069)	(0.059)
	N	*503*	*448*	*448*	*368*	*195*	*503*	*503*	503
Grade 10th language arts test		0.482***	0.475*	0.251	-0.155	-0.377	-0.028	-0.035	-0.133
< Sample mean		(0.152)	(0.245)	(0.165)	(0.242)	(0.398)	(0.072)	(0.052)	(0.095)
	N	*500*	*369*	*369*	*240*	*125*	*500*	*500*	500
Grade 10th mathematics test		0.305***	0.437***	0.219**	0.311**	0.376*	0.133	0.177**	-0.120**
≥ Sample mean		(0.075)	(0.123)	(0.087)	(0.136)	(0.192)	(0.087)	(0.073)	(0.055)
	N	*504*	*409*	*409*	*342*	*183*	*504*	*504*	504
Grade 10th mathematics test		0.518***	0.314	0.154	-0.207	-0.383	0.021	-0.023	-0.010
< Sample mean		(0.136)	(0.248)	(0.171)	(0.241)	(0.400)	(0.061)	(0.031)	(0.110)
	N	*499*	*408*	*408*	*266*	*137*	*499*	*499*	499

Note: Each point estimate is from a separate regression. All models condition on school fixed effects, grade 9-10th avg. GPA with separate linear splines above and below the threshold, and student controls. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

A7. Reduced-form RD estimates by complier status

	EDT=0	Observations
High school, Grades 11th and 12th GPA		
Mathematics	0.302** (0.128)	748
Language arts	0.155 (0.100)	748
University entrance exam		
Std. mathematics test score	0.144 (0.111)	576
Std. science test score	0.426** (0.200)	307
Higher Education matriculation		
CRUCH university	0.080 (0.075)	970
Top-tier, highly-selective university	0.097 (0.061)	970
Technical training center	-0.072 (0.060)	970

Note: Each point estimate is from a separate regression. All models condition on school fixed effects, grade 9-10th avg. GPA with separate linear splines above and below the threshold, and student controls. The second column shows RD estimates for separate samples of students who did not uptake the EDT program (EDT=0). Robust standard errors are in parenthesis. ***p<0.01, **p<0.05, *p<0.1