“The Effects of Remedial Math on Student Outcomes: Evidence from an Higher Education Institution in Chile using Regression Discontinuity Design”

TESIS PARA OPTAR AL GRADO DE

Magíster en Análisis Económico

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Santiago, Diciembre 2019

The Effects of Remedial Math on Student Outcomes: Evidence from an Higher Education Institution in Chile using Regression Discontinuity Design

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Abstract

For countries concerned about equity and access to higher education, providing support services for academically underprepared students is key to increase their probabilities of success. Remedial courses provide opportunities for underprepared students to develop their basic skills in their initial semester of enrollment. However, adding additional coursework like a remedial course may increase students' academic workload, a decrease in their academic performance, or directly slow them down, increasing their probabilities to drop out. Our study explores the consequence of being assigned to a remedial math course in a context of a fixed curriculum. This allows us to explore the effect of remediation course taking on the same courses and credits that non-remedial students take, providing a more accurate landscape of the impact of remedial course policy. Using a unique administrative dataset from one of the largest vocational education postsecondary institutions in Chile, we examine the effects of enrollment in remedial courses on diverse student outcomes employing a Regression Discontinuity (RD) design exploiting an institutional cutoff. Our results show that being assigned to the remedial course increases student's grades in their subsequent math course and decreases the likelihood of desertion during the first semester, but the retained students seem to leave the semester right after. These results are promising for a math remedial policy, which has to be carefully balanced with additional support to avoid students from feeling overwhelmed and drop out a semester after.

Keywords:
Remedial courses, Higher education, Mathematics, Regression Discontinuity

1. Introduction

The vast number of students entering higher education who are academically unprepared for college-level work has created a strain on postsecondary institutions and the students they enroll. McCabe (2003) shows that nearly half of the students entering community colleges are underprepared, and current estimates suggest that more than half of all undergraduates and 70 percent of community college students in the United States take at least one remedial course while in college, due to been cataloged by their institutions as underprepared, creating greater costs for higher educational institutions (National Center for Education Statistics[1], 2003; Bailey, 2009; Scott-Clayton & Rodriguez, 2015). In response to this, community colleges disproportionately serve students who require these student support programs to develop their skills in one or more areas. Such support services include peer mentoring, proactive advising, tutoring and remedial courses (Bettinger et al., 2013).

Remedial courses are typically mentioned as the gateway by which academically underprepared students begin their postsecondary study, and have the purpose of improving their abilities to handle college-level material and succeed (Bettinger et al., 2013). Remedial education is an important component of higher education that promises to re-open opportunities to those students who begin a degree already academically behind their peers, especially in mathematics given the minimum mathematic requirements of most college degree programs and the low-level of mathematic skills among many entering students.

Remedial courses have been posed as a solution, but the existing evidence is not clear about its effects on student's outcomes. For example, studies have shown that students who take part in a remedial course tend to present higher retention, degree completion rate, credit accumulation, grades and success in college-level courses and lower transfer rates (Bettinger & Long, 2009; Martorell & McFralin Jr., 2011; Edgecombe et al., 2013; Belfield et al., 2016). But also negative effects for the same outcomes have been found in several studies (Scott-Clayton & Rodriguez, 2015; Duchini, 2017; Boatman & Long,

[1] NCES

2019).

There are several models of remedial education. One of the most common models is the prerequisite model, whereas its name indicates, the remedial courses are defined as a prerequisite of every college-level course of the student's program. A limit of this model is that it forces students to spend two or even three extra semesters passing remedial courses that usually do not add credits to the student's college coursework (Martorell & McFralin Jr., 2011). While being enrolled in remedial courses, students accumulate debt and deplete their chances to be selected for financial aid. Moreover, many students can become discouraged when they learn that they must delay their college education (Deil-Amen & Rosenbaum, 2002; Bailey et al., 2010).

A more recent model, implemented in at least 300 different schools[2] is the corequisite model. In this model, students move straight to the college-level courses in the first semester with a remedial course, which is provided alongside the college-level course (Daugherty et al., 2018; Cho et al., 2012)[3]. While this model prevents some of the extra semesters caused by the prerequisite model, it still has its limitations. Indeed, the fact that it provides support services for underprepared students tailored to a specific college-level course, instead of a stand-alone prerequisite remedial courses, could cause a non-exposure to some important academic material (Logue et al., 2019).

Moreover, there is a fairly new and yet untested remedial education model implemented at Duoc UC in Chile. This particular model attempts to prevent some of the possible costs from the prerequisite and corequisite models, by including the remedial course in the fixed and mandatory coursework. Students from the same major are required to take the same non-remedial courses simultaneously. The fact that the enrollment in the remedial course is the only difference among students from the same major, prevents them from taking extra semesters, but it also increases the workload during the first semester.

[2]For a complete list, visit http://alp-deved.org/alp-schools-directory.

[3]The most well-known corequisite model is the Accelerated Learning Program (ALP), developed by the Community College of Baltimore County.

Isolating the effects of taking a remedial course has been difficult to study. In particular, due to selection bias (Jepsen, 2006), not been able to compare between the treatment and control groups (Michael & MacDonald, 1995) and even ambiguously or inconsistently defined placement policies (Bettinger & Long, 2009). Thus, it is difficult to identify the insights derived exclusively from earlier studies. This research takes a step toward uncovering those insights by leveraging on an institutional cutoff and using a sharp regression discontinuity design to obtain evidence on the effects that this new remedial education model has on students.

To the best of our knowledge no study has analyzed the heterogeneity of results. Our study is the first to reveal gender and socioeconomic differences as well as difference between night and day shift, and length of program.

Based on data of first-time students from 2010 to 2016, we observe that students who were forced to enroll in the remedial class obtained better outcomes than the ones who managed to skip it. With the academic support, students show higher grades in their first college-level mathematics course and were more likely to stay in Duoc UC in the first semester. Moreover, students show no clear negative effects, compared with those observed in previous studies. Taken together, these results are relevant evidence on the effects of a new remedial model and how it can help underprepared students who are beginning their higher education.

This paper is organized as follows: We begin reviewing earlier studies on remedial courses in Section 2. Section 3 illustrates an overview of the Chilean and Duoc UC's context. In Section 4 we describe the dataset used in this study and present the analytical strategy, along with the outcomes of interest. Section 5 documents our findings, and Section 6 ends the conclusion.

2. Literature Review

This paper adds to the existing literature that estimates the effects of remedial courses on students' outcomes using a Regression Discontinuity (RD) design. Given that randomized trials in this area are scarce (Valentine et al., 2017) and because higher education institutions typically assign students to remedial education based on a certain test score, regression discontinuity designs have become a popular identification strategy for estimating the effects of remedial education. De Paola & Scoppa (2014), using a fuzzy regression discontinuity design, find that remedial programs in the University of Calabria in Italy have a large and positive effect in the credit accumulation and persistence in college.

Jepsen (2006) compares community college students from California who took a remediation course to those who were referred to remediation by the college's staff but decided not to enroll in remediation. His results show a positive effect of the remedial course in college persistence and degree completion but are subject to selection bias. Because these remediation courses were optional to the students, those who decided to enroll in the remedial course could have relatively high levels of academic motivation, which is not observed in the data.

Boatman & Long (2019) study the effect of remedial courses on college students with different levels of academic preparedness. Through an RD design, they found negative effects on student retention and no effect on math course completion. However, when they consider a student with lower levels of academic preparation, they estimate positive and statistically significant effects of remediation. On the other hand, Duchini (2017) fails to find any positive or significant results of a remedial program for an undergraduate economics program at a university in Italy. Scott-Clayton & Rodriguez (2015) results, similarly to Martorell & McFarlin Jr. (2011), indicate that remedial courses fail to develop student's academic skills sufficiently to increase their rates of colleges. Also, they find that students who participate in these remedial courses tend to have an eight percentage point increase in the probability of dropping out of college. Valentine et al. (2017) provide a systematic review and meta-analysis of different studies that use regression discontinuity designs to obtain the effects of placement in remedial courses on students' outcomes. They obtain negative, statistically significant effects of the large magnitude of the different remedial programs in the likelihood to pass following math courses, the amounts of credits passed and other academic attainments.

We also add to this literature by being the first study in Chile measuring the impact of a remedial course model in higher education. In Chile, one study of a remedial program for university dental students found positive academic results for students participating in a remedial program, although the study concerned only 21 dental students who had recieved a grade below sufficient on at least one of three exams, and the remediation program was not particularly well defined. Mean grades among those 21 students had improved and were, in fact, higher than the students who did not receive the interventions (Alcota, Muñoz, & González, 2011). A descriptive study by Duoc UC in 2005 observed that students who completed the remedial Math 100 course received a final grade that was not statistically different from the grades of the students who already demonstrated sufficient mathematic level.

3. Chilean and Duoc UC context

The current education system in Chile took shape during reforms in the late twentieth century. In 1981, the Chilean government enacted educational reforms intending to redistribute resources among all levels of public education and to increase efficiency at the postsecondary level. The reforms encouraged the participation of the private sector, which would provide new educational opportunities and redistribute public resources that could be reallocated to lower levels of public education. As such, these reforms expanded the higher education sector to include more options for students graduating from high school [4]. Both enrollment and tuition increased during this period (Fried & Abuhadba, 1991).

The three main types of postsecondary institutions in Chile are universities, professional institutes, and technical training centers. Universities offer five-year undergraduate, two-year master's, and four-year doctoral degrees; professional institutes offer four-year professional degrees, technical training centers offer two-year skill-based degrees. Some of these institutions operate entirely on private funds while some receive public support (Crawford & Mogollón, 2009). Today, there are 53 accredited universities, 17 accredited professional institutes, 12 accredited centers for technical training, and over 100 unaccredited institutions (Ministry of Education of Chile, 2012).

[4] Between 1980 and 1989, enrollment in higher education in Chile increased 96 percent.

The diversification of institutions presented more opportunities for low-income students and has allowed enrollment of students in the two lowest income quintiles to increased fivefold between 1980 and 2009.

This shift introduced more students who had received low quality primary and secondary educations, meaning more students received low scores on the national entrance exam and required remedial support than ever before. In recent years, Chile has begun to provide additional supports for these students at all levels of schooling, including primary, secondary, and post-secondary levels (Crawford & Mogollón, 2009; Ministry of Education of Chile, 2012).

The institution in our study, Duoc UC, is a non-profit Vocational Education and Training institution that operates as a Technical Education Center and as a Professional Institute. The Institute was initially created in 1968 to extend education to students from socioeconomic sectors that did not have access to higher education. It has no admissions requirements, and all students are accepted on a first-come-first-served basis. Duoc UC offers 75 different programs in nine different degree programs, similar in content to community college associate degrees in the United States[5]. Duoc UC currently serves more than 84.156 students through 16 campuses in five cities. Students are primarily from middle and low socioeconomic sectors of the Chilean population.

3.1. Remedial Courses

Due to Duoc UC's open admissions policy across all its campuses, the institution must educate a wide range of students with different levels of prior academic preparation. To address this issue, they offer a remedial math course to help those students who enter college with low math skills. In 2001, before the remedial courses were implemented, the mean pass rate of mandatory/introductory college-level math courses across the Duoc UC campuses was 60%, with an average grade of a 4.5 out of 7 (or the equivalent to a C). In 2003, Duoc UC implemented a remedial course intended to cover

[5]The degree programs include business/administration, communication/publicity & public relations, construction, design, computer science, engineering, natural resources, health, and tourism.

high school-level math concepts in the first semester of college. The objectives of the remedial math course were both to increase the math skills of students who were behind, but also to increase their general study skills and social networks (Duoc UC, 2005). The remedial course requires 6 hrs/week of lecture, and no class is larger than 40 students per section. The remedial math course (Basic Math, or Math 100) is offered during the first semester only and students attend the course in parallel to the required courses that other students in their major are attending.

Every year, all new students, regardless of their area of study, are given a diagnostic test a few days after their enrollment to assess their math skills. Students are exempt from taking remedial Math 100 if they score at or above 70% (70 points out of 100) on the multiple-choice diagnostic test, while students with scores below 70% are required to take the remedial math course [6]. Students who skip the test are automatically registered in the remedial class[7]. Additionally, the mandatory/ introductory math course was moved to the second semester of the first year, meaning that all students, regardless of their placement test score, come together in the second semester of their first year in a common college-level math class.

All students in remedial Duoc UC's math remediation model are taught the same material. The course is designed in a central department for all campuses and programs, and every student takes the same final exam at the end of the course to determine successful completion. Students who fail a remedial math course can retake it during the second semester. This particular math remediation model, also has four unique characteristics: (1) students who attend remedial classes are not delayed in their program (2) students who attend remedial classes have a greater workload (one additional course) during the first semester than students who are exempt from these classes (3) all students in the same major attend all required classes of their program together at the same time, despite being in a remedial class or not (due to the inflexibility of the curriculum) (4) students who are assigned to remedial math must wait a semester before they can enroll in their first college-level

[6] Given this rather high placement cutoff, the majority of students are placed into remedial Math 100 In 2003, only 5% of the students were exempt from the remedial math course. Today about 75% of students are placed into remedial math 100.

[7] About 30% of students do not take the placement exam each year.

math course (for example Algebra or Math 200).

Given the structure of the remedial courses in Duoc UC, we examine whether students at the margins of being placed into the remedial math course benefit from the opportunity to practice their math skills for a semester such that these students ultimately outperform their peers who did not take a math class for a semester. Our study is similar to prior research conducted on U.S. institutions on the effectiveness of remedial math courses, but we examine the effects of these courses on students pursuing technical and professional degrees in Duoc UC. The goal of our study is to understand if remedial courses can assist students in successfully earning higher grades in their college-level math courses than their peers not assigned to remedial math. Specifically, we strive to answer: Does participation in a remedial math course improve course performance in the next course for students at the margins of passing the placement test?

4. Data & Empirical Framework

4.1. Data

This study draws on three different datasets, all provided directly from Duoc UC. These datasets are: (1) socio-demographic information of students, which is all pre-treatment and reported by themselves at the time of enrollment (high school type[8], household income, age, parent's education, gender and high school GPA); (2) administrative information including general degree registered, campus, cohort in which the student enrolled in Duoc UC, mode (night or day shift), academic information for each Duoc UC course ever taken by the student (including final grades, credits, indicator if the student failed a course due to non-attendance, etc.); (3) placement test scores of each incoming student who took the diagnostics test in Mathematics and Language.

We limit the main analytical sample to first-time Duoc UC students who have taken the diagnostic test, at any of the 16 Duoc UC campuses, between Fall 2010 and Fall 2016, which adds up to 54.971 students. We only consider

[8] Private, Subsidized and public.

students from the Business & Administration, Engineering and Informatics & Telecommunications departments, so we could assure that all students in the sample were enrolled in a degree with at least one mathematics course after the remedial. Table 1 describes the population by cohort. While the number of students seems to duplicate in 5 years, the characteristics of cohorts remain similar across years.

[**Table 1**]

Table 2 describes the analytical sample showing the differences in socio-demographic, high school, and enrollment information variables for all pulled cohorts divided by the two groups: Students above and below the cutoff score. Students below the cutoff score are more likely to be female, less likely to have mothers with finished high school, more likely to enroll in Duoc UC right after graduating from high school. Not surprisingly, they also tend to have a lower highschool GPA[9].

[**Table 2**]

We recognize that the effects of placement into remedial courses may be different for different groups of students. For example between men and women; students enrolled in the day or night shift; students enrolled in a professional or technical degree; students with and without mothers who finished high school. We include all these different groups of students in the analysis and test if there are any heterogeneous effects between these groups.

4.2. Outcome Measures

This study examines the effects of remedial courses on students' Desertion & Graduation; Credit accumulation & GPA; and academic success in their Next Mathematics Course after the remedial. These outcomes are tied to the direct effects we might expect the remedial course to have on students in remediation as compared to their peers who just passed the placement exam.

[9] "Notas de Enseñanza Media", which translates to Grades from High school.

Also, unlike prior research, we have the particular advantage that all students in our sample take the same courses simultaneously, with enrollment in remedial math being the only difference among students of the same academic major. This allows us to better understand the true effects of remedial courses on subsequent course grades, as there is no variation in the courses students take in the Chilean campus in our sample.

Given that the design of the remedial course results in a greater workload for lower-skilled students, and because it is possible that this course could overwhelm the students and force them to leave their degree or even the institution itself, considering outcomes related to students persistence becomes crucial. In the works of Jenkins et al. (2009) and Boatman & Long (2019) it is mentioned that the remedial courses in their pursuit to support students, they end up slowing them down in their early progress toward a degree so much that they become discouraged and drop out of college. We consider both drops out during the semester of enrollment in remedial math, as well as drop out during the first year to account for student persistence during and after remedial math enrollment.

Furthermore, taking this extra course could increase the workload to the point at which the students can not cope with it, and tend to pass the fewer amount of credits. Duchini (2017) mentions this as one of the main reasons why the assignment to remedial courses might increase the students' chances of dropping out. One of the main results in her work is that the students placed in the remedial course tend to accumulate fewer credits compared with the students who avoid it. Therefore we consider the number of credits approved by the students during their first and second semesters in Duoc. Also, to make sure that the effects of the remedial course in the students' credit accumulation are due to an excess of academic workload and not to an over-focus from the students in the remedial course, ignoring the others, we include the students GPA with and without the remedial course.

Finally, we consider the academic success in the subsequent mathematics course of the students given the very closely tied to the whole purpose of remediation course: development of subject-area skill. The sole purpose of remedial coursework is to help the students who begin a degree with a clear disadvantage in knowledge, to catch up with their classmates. Consequently, we would expect that remedial course enrollment would affect students, at very least, in their grades in their next math course, which tends to be one of the greatest obstacles (Ngo, 2018; Association of Colleges and Universities, 2016).

4.3. Analytical Strategy

Determining the causal impact of remediation on student outcomes is difficult due to the observed and unobserved differences in the students assigned to remediation, as compared with students assigned to college-level courses. Simply contrasting the average outcomes of this two different groups[10] ignores the problem of selection and tells us nothing about whether differences in student outcomes were caused by students' enrollment in the remedial math class.

To account for this potential bias, we apply a quasi-experimental design using a Regression Discontinuity (RD) framework. We take advantage of the discontinuity or threshold for entering remedial math courses in the first year of Duoc UC programs depending on the diagnostic test on the first's days after the student enrolled. This RD design allows for an identification strategy that compares the outcomes of those who fell just short of the threshold score (and had to take remedial mathematics) against those who just passed the threshold score (and were exempt from the class). Since these two populations (right around the cut-off) are arguably indistinguishable with regards to their initial abilities and unobservable determinants of future performance, this approach allows for rigorous non-biased estimation of the impact of being registered for remedial courses (Shadish et al., 2002; Murnane & Willett, 2011; Urquiola & Verhoogen, 2009; Lee & Lemieux, 2010).

To address our research questions, we use the following model:

$$y_{ijkh} = \beta_0 + \beta_{1j} S_{ijkh} + \beta_2 C_{ijkh} + \beta_3 C_{ijkh} * S_{ijkh} + \beta_4 Z_{ijkh} + cohort_j + degree_k + campus_h + \epsilon_{ijkh} \quad (1)$$

[10]As presented in the Duoc UC (2005) study.

Where y_{ijkh} is the outcome for the i^{th} student of the j^{th} cohort, the k^{th} general degree and the h^{th} campus, S_{ijkh} is the score on the placement exam centered at the cutoff (70 out of 100), C_{ijkh} is a dummy that equals 1 when the student achieves a score below the cutoff, and Z_{ijkh} includes exogenous covariables describing student gender, age, high school NEM, etc. Also, $cohort_j$ controls for the cohorts fixed effects, $degree_k$ controls for the general degree fixed effect, and $campus_h$ controls for the campus fixed effects. We estimate the effect of being selected for remedial math on outcome y_{ijkh} and ϵ_{ijkh} is the first-stage residual.

Next, we test the internal validity of our RD design by testing several conditions that need to be met according to the works of Bloom (2012) and Schochet et al. (2010). First, we need to ensure that the diagnostic test score is not influenced by the treatment. This condition is met the score of the diagnostic test occurs before the treatment starts. The second condition demands that the cutoff score be determined independently of the running variable. This condition is met because the cutoff score was determined even before the students took the diagnostics test. The third condition to ensure the internal validity of our regression discontinuity design is that the running variable should have been generated ignorable randomly around the cutoff. This ensures us that the students that failed the diagnostic test are not systematically different from the ones that passed.

We test for violations of these conditions in three different ways. First, we need to ensure that there has not been any kind of manipulation of the test scores. In this case, the students' tests are evaluated through a machine, which eliminates the possibility that any person could assign the students' a certain score just under or over the cutoff score. In Figure 1 we look at whether there is any sign of a visible jump in the density around the cutoff for all cohorts separately. As can be seen, there are no signs of any jumps in the density at the cutoff point. We also run a McCrary (2008) test, and we are able to confirm the same results that the histograms in Figure 1 showed us.

[**Figure 1**]

Next, we test whether the pre-treatment characteristics of the students' are the same between the treated and non-treated group[11]. In order to meet the assumptions of our identification strategy and avoid any contamination of the results, we need to ensure that the treated and non-treated groups are statistically similar near the cutoff point.

In Figure 2, we show the fitted values of the students' pre-treatment characteristics from a local linear regression, using the optimal bandwidth, between each characteristic and the interaction of the running variable with the indicator of being above the cutoff score. Here the optimal bandwidth, following Calonico et al. (2014), is around 12.5 points above and below the cutoff.

[**Figure 2**]

Table A.8 repeats the same process considering different bandwidths. Among 132 models that tested 11 covariates, we find that only one model with statistically significant imbalances. The percentage of students with mothers that completed postsecondary technical education is significantly higher for students above the cutoff score in this one different model.

[**Table A.8**]

Finally, even when the vast majority of the models show that there is no significant imbalance among the two groups, this may be due to the number of observations, and hence statistical power. To eliminate this possible threat, we test if these results are a true reflection of the possible imbalance that could invalidate the whole regression discontinuity design in this study. To achieve this, and following the work of Dee & Sievertsen (2018), we obtain an "Outcome Index" which is a weighted average of all the covariates in the model and indicates the extent to which the covariables predicts the outcome among the students. To create this "Outcome Index", we regress each outcome variable by the covariables, to later obtain the predicted outcome of these regressions.

The index is a weighted average of all the different covariates in the model,

[11]Here, the fact of being forced to take the remedial course is considered as the treatment.

where the weights are defined as how much each covariable can predict the outcome among students. It is created by regressing every outcome considered against the baseline covariable and then we predict the outcome. This predicted value corresponds to the "Outcome Index". The estimates for all the subsamples considered can be seen in Table 3[12].

[Table 3]

4.4. First Stage

As it has been mentioned before, the students of Duoc UC are obligated to attend the remedial mathematics course if they score less than 70 points in their diagnostics test, which theoretically points to a "Sharp" discontinuity, there are some cases where students enroll themselves in Duoc UC after the diagnostics test is held and they are forced to take the remedial course. Also, other students did score 70 or more in their diagnostics test but didn't go through the proper channels to cancel their enrollment in the remedial course, and have to take it anyway. There are 8.483 students in the dataset who score 70 or more and among those students only a 1.93% (164) where enrolled in the remedial course. We calculate the impact of being above the 70 cutoff score on the probability of not been enrolled in the remedial course.

Figure 3 shows the predicted probability of being enrolled in the remedial course by the diagnostics test score. This graph clearly shows a significant discontinuity at the cutoff score. Which proves that our forcing variable is in fact a good indicator of being assign to treatment.

[Figure 3]

5. Results

In the following section, we present the results of our main regression, where we estimate the effect of the remedial math course on the different outcomes of the students here in Duoc UC. We hypothesize that the students who enroll in the remedial course should have been able to develop

[12]Figure 3 plots this index against the running variable in the Appendix.

the foundational skills and knowledge that they may have lacked when they originally took the placement test. Consequently, we might expect them to at least catch up with their better-performing classmates, if not surpass their performance in subsequent math coursework. This development should allow treated students to pass their next math course, which in many cases is one of their greatest barriers to academic success and attainment. We also believe that the students who were forced to take the remedial course will have higher grades for their mathematical courses and a lower drop out rate during their first semester and first year.

We present 10 different discontinuities for each one of the studied outcomes. For each of these outcomes, we consider 5 different bandwidths (including the optimal bandwidth), presented with and without controlling for covariates. All the results of our estimations can also be viewed graphically in Figure 4.

[**Figure 4**]

5.1. Desertion & Graduation

The first section presented in Table 4 show the results for desertion during the first semester and year, and the completion of the students' coursework. We can observe negative and statistically significant results only for the desertion in the first semester. Students who were forced to take the remedial course are 2.3 percentage points (Optimal Bandwidth, Columns 3 and 8), which translates in a 25% drop in desertion during their first semester compared to the students who manage to skip it. These results are stable without or with controlling for covariables, in all bandwidths. Desertion in the first year and completion of the course work show no statistically significant results in any bandwidth.

5.2. Credit Accumulation & GPA

In the second section of Table 4 presents the estimated results for students' credit approval in the first and second semester and the students' GPA for the first semester with and without including the remedial mathematics course. We see no statistically significant effects on the number of approved credits in the first semester. For the number of approved credits in the second semester we see positive and statistically significant effects for two of the five bandwidths (5 & 20), where we see that students who took the remedial course tend to approved 1.636 and 0.689 respectively.

As for the students' GPA during the first semester, with and without the remedial course, we see that a positive and statistically significant effect for the GPA that includes the remedial course. This effect shows that the students treated with the remedial course tend to obtain 0.141 (Opt. Bandwidth) points more than the students who skipped the course. Unlike the effects for the GPA with the remedial course, the GPA without this course shows no statistically significant effects in any bandwidth.

5.3. Next Mathematic Course

The final section in Table 4 shows that students placed in the remedial course managed to obtain, on average, 0.080 points more than the students that didn't take the course, in their next mathematics course GPA. This positive and statistically significant effect can be viewed in 3 of the 5 estimated bandwidths, including the optimal bandwidth, and also stable whether we include or do not include the covariables in the estimation.

Not only the effect is in the direction we were expecting, but also these results show that the remedial course helped the students to catch with their classmates, and even surpass them. There are no statistically significant effects in the likelihood of the student getting a passing grade in the next math course.

[Table 4]

5.4. Heterogeneous Effects

We recognize that the effects of this remedial mathematics course may be different for certain groups of students, and because of this we proceed to report results by these diverse groups. We first see if there are gender differences, given that drop out rates are different for men than women in these math oriented programs (12.2% vs 8.9%). We will also analyze separately the day shift programs from the night shift, because student groups differ in many characteristics. Night shift students have been away from formal studies for a long time. Their average age is 24 years old (in contrast to the 20 years old in the day shift) and they present a drop out rate of 14.7% versus the 8.3% in the day shift.

The estimates results are obtained from the same model used in Table 4, but only for the just mentioned subsamples. Therefore we calculated a new optimal bandwidth for each subgroup, which are all reported at Table 5.

In the first section of Table 5 we explore whether the desertion during the first semester, year and the completion of the students' coursework present any evidence of heterogeneous effects across the different subgroups. Comparing the results of these new estimation results with the ones presented in Table 4.

As shown in Table 5, the effects of the remedial course vary among student groups. For example, between students from the day shift and the night shift. Night shift students seem to benefit widely from being assigned to the remedial course. We see a decrease of 4.9 percentage points in the drop out rates for the first semester, without showing a decrease in credits approved or GPA. On the other hand, day shif students seem to get only the negative consequences of having an extra course in the first semester compared to their peers. They complete less credits during the first semester and lower GPA, when the remedial course is excluded. It is possible that students from the night shift, who are older and have been longer time away from academic studies[13], may take greater advantage of a remedial course, despite having to complete additional credits.

[Table 5]

5.5. Graduation Outcomes

In Duoc UC, the professional degree programs require at least four years of enrollment to complete the coursework. Because we have students academic information up until the year 2018, and our sample is composed of

[13]Students from the night shift show a statistically significant difference of 4.41 years with the day shift.

students who entered the institution between the year 2010 and the year 2016, the students from professional degrees who entered in 2015 and 2016 did not have the minimum amount of time to complete their coursework, which could be affecting our earlier estimations results.

Thus, in this section we will only consider the cohorts where all students had the opportunity to finish their respective coursework, giving us a confirmation sample of 33.373 students. By doing so, we seek to obtain unbiased estimation results of the effect that the remedial mathematics course placement has on completed coursework and also to confirm our previously estimated results.

As before, we check the balance of every covariable considered in the estimations of this study, and across all bandwidths. The balance checks largely show the same results as our previous specifications, except for three models. However, the balance check for the outcome index confirms that they are no statistically significant differences in the characteristics of students who just barely failed the diagnostic test and those who barely passed it[14].

The results in the first section of Table 6 show the same trend as the original results, however fewer specifications yield statistically significant effect estimates. The Optimal Bandwidth shows no statistical significance any of these section outcomes, and only 2 other bandwidths show a statistical significance for the desertion during the first semester.

The second section of Table 6 shows almost no difference, in magnitude or statistical significance, with the original results. The most significant difference can be viewed in the third section. In our original results, we observe that the standardized students' GPA in their subsequent mathematics course had a statistical significance in only 3 of the bandwidths. But in Table 6 we observe that when the covariables are not included in the estimation, all bandwidths show statistical significance, and when we include the covariables the statistical significance only appears in the Optimal Bandwidth and the 20 points bandwidth.

[14] All validation test results can be viewed in Tables A.10-A.13.

[Table 6]

We also ran new estimations for all subgroups mentioned in Subsection 5.4, so we could confirm the results. As shown in Table 7, the estimation results tend to follow the results obtain in Table 5, but with less statistical significance in most of the results.

6. Conclusion

The effects of college remediation on desertion, coursework completion, credit accumulation, GPA and academic performance in certain areas are of utmost interest to administrators and policymakers. Especially since remedial education has been a growing featured of education at higher education institutions around the world. We examine the particular remedial program implemented at Duoc UC, where the remedial course is included in the fixed and mandatory student's coursework, and enrollment in remedial math being the only difference among students of the same academic major. This particular remedial education model allows us to avoid various limitations presented in former studies.

Also, unlike prior research, we have the particular advantage that all students in our sample take the same courses simultaneously, with enrollment in remedial math being the only difference among students of the same academic major. This allows us to better understand the true effects of remedial courses on subsequent course grades, as there is no variation in the courses students take in the Chilean campus in our sample.

The current literature has primarily estimated the effects of remedial education on students in college in the United States. Our paper contributes to prior evidence from various studies on the effects of students placed in remedial mathematics courses by estimating the effects of being just below the cutoff score for students in set course sequences at a system of Chilean technical colleges.

We find that remedial math placement improves some aspects of students' academic achievement. The most important effect is the one regarding the academic achievement of students in their subsequent mathematical courses.

The remedial course seems to have a positive and statistically significant effect of 0.056 points in the next mathematics course GPA's.

In regards to the likelihood of desertion and coursework completion, this remedial course appears lower the likelihood of initial desertion in the first semester by 2.3% when compared with students who are ready for college-level mathematics courses. But unfortunately, these effect seems to fade out showing no statistically significant effect in the likelihood of students finishing their coursework or in the likelihood of desertion during the second semester.

In an attempt to understand this fading out of the effect in desertion we obtain the effects of the remedial course for credit accumulation, but we were not able to find any negative and statistically significant effects for students who were forced to take the remedial course. Although we find that placement in the remedial course does have a positive and statistically significant effect in the students' GPA of 0.139 points, when including the remedial course in the GPA. But this significance disappears when we exclude the remedial course grades from the students GPA, which suggest an overcommitment from the students to this remedial math course.

We also observed evidence that some outcomes estimated results could differ for certain subgroups of students. The two main differences are between the students enrolled in day shift degrees with the students in the night shift degrees. This subsamples showed opposite and both statistically significant effect in the number of credits accumulated during the first semester, and the students' GPA without including the remedial course. We hypothesize that this effects were due to the difference of age that students from the night shift have with the day shift (Students in the night shift are on averge 24 years old, four years older than the ones from the day shift), which could have made the remedial course that much more effective in helping the students from the night shift to remember basic mathematic skills. In addition, we believe that the difference in the effects of the remedial course between the students from the day shift and the night shift could have been caused in part due to the possible difference in perseverance, even in the face of adversity, of these two groups.

Our analysis shows that the estimated effects have no clear negative and significant effects, compared with those observed in previous studies. Past evaluations of remediation courses have shown certain degrees of selection bias and ambiguously or inconsistently defined placement policies (Michael & MacDonald, 1995; Jepsen, 2006), which has resulted in controversy regarding the benefits of remedial courses. Our article attempts to remedy this, by providing more stable and unbiased results thanks to the coursework structure and the implementation of the remedial course program in Duoc UC.

The findings obtained in this study are particularly important for all higher education institutions in today's world, as more and more students who enter college or community college are academically unprepared for college-level work. Eliminating most of the selection bias, we can obtain more credible results regarding the effects of remedial courses in some of the most important student's outcomes. One implication of our study is that higher education institutions should rethink the implementation of their remedial programs, as most of them do not include the remedial course inside the student's coursework, but offered them as optional and as an extracurricular activity. However, there still remain questions regarding how effective these remedial programs are when considering the student's perseverance of effort.

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8. Tables

Table 1: Distribution of DUOC UC Students by Cohort

Cohorte	(1) Num. Stud.	(2) % Women	(3) %Comp Coursework	(4) %Mother HE	(5) %Tec. Dg.	(6) %Day Shift	(7) %Inm. Enrollment	(8) %Inm. Enrollment
2010	5,893	0.28	0.57	0.60	0.67	0.50	0.82	0.29
2011	4,561	0.31	0.59	0.59	0.67	0.51	0.80	0.40
2012	6,265	0.30	0.58	0.61	0.68	0.50	0.81	0.40
2013	8,642	0.32	0.55	0.62	0.72	0.50	0.90	0.33
2014	8,012	0.30	0.51	0.61	0.75	0.49	0.88	0.34
2015	11,066	0.28	0.28	0.63	0.71	0.54	0.87	0.36
2016	10,532	0.27	0.15	0.62	0.70	0.57	0.82	0.38

Notes: HE=High School Education; UE=University Education; TE=Technical Education. NEM is the equivalent in Chile of the GPA in the United States. a=These Cohorts have not had the time to finish their programs which is 4 years for professional and 2.5 years for technical programs.

Table 2: Summary Statistics for Covariates among Students in Analitycal Sample

Variables	**(1) Full Sample**			**(2) Below Threshold**			**(3) Above Threshold**			**(4) T-test**
	count	mean	sd	count	mean	sd	count	mean	sd	p
Female	54,947	0.292	0.455	46,466	0.310	0.463	8,481	0.192	0.394	0.000
Mother wiht HE	53,790	0.614	0.487	45,422	0.594	0.491	8,368	0.722	0.448	0.000
Mother wiht UE	53,790	0.055	0.228	45,422	0.046	0.209	8,368	0.103	0.304	0.000
Mother wiht TE	53,790	0.126	0.332	45,422	0.119	0.323	8,368	0.169	0.374	0.000
Father wiht HE	53,759	0.603	0.489	45,392	0.585	0.493	8,367	0.701	0.458	0.000
Father wiht UE	53,759	0.071	0.257	45,392	0.060	0.238	8,367	0.129	0.335	0.000
Father wiht TE	53,759	0.112	0.315	45,392	0.106	0.307	8,367	0.144	0.351	0.000
Immediate Enroll.	54,964	0.355	0.478	46,481	0.361	0.480	8,483	0.319	0.466	0.000
Age	54,964	22.456	5.228	46,481	22.457	5.251	8,483	22.448	5.096	0.886
NEM Avg.	54,435	5.432	0.410	46,036	5.400	0.399	8,399	5.612	0.426	0.000
Family size	53,799	4.105	1.562	45,430	4.126	1.576	8,369	3.991	1.480	0.000
Enrolled in Prof. Degree	54,597	0.293	0.455	46,404	0.273	0.446	8,193	0.405	0.491	0.000
Enrolled in Day Shift	54,597	0.521	0.500	46,404	0.509	0.500	8,193	0.587	0.492	0.000
Next Math C. Grade	41,606	4.789	1.255	34,393	4.644	1.237	7,213	5.479	1.103	0.000
Desertion 1st. sem.	54,964	0.113	0.316	46,481	0.123	0.328	8,483	0.058	0.234	0.000
Desertion 1st. year	54,964	0.075	0.264	46,481	0.079	0.270	8,483	0.054	0.226	0.000
Credits approved 1st sem.	54,597	34.296	13.847	46,404	33.997	14.231	8,193	35.988	11.287	0.000
Credits approved 1st year	47,301	75.361	21.246	39,708	75.147	21.336	7,593	76.478	20.735	0.000
Completed Coursework	54,964	0.420	0.494	46,481	0.404	0.491	8,483	0.509	0.500	0.000

Notes: HE=High School Education; UE=University Education; TE=Technical Education. NEM is the equivalent in Chile of the GPA in the United States. Last column correspond to a T-test of means between the students that are above and below the threshold for every variable.

Table 3: Outcome Balance Index

Outcomes	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20
Desertion & Graduation					
Deser. 1st sem.	0.000	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Deser. 1st year	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Completed Full Program Coursework	0.001	0.001	0.001	0.000	0.002
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
N	5747	10545	13247	16372	22437
Credit Accumulation					
Credits approved 1 s. (w/o Rem.)	0.014	0.022	0.010	0.002	0.016
	(0.046)	(0.031)	(0.028)	(0.025)	(0.022)
Credits approved 2 s. (w/o Rem.)	0.038	0.056	0.044	0.020	0.064
	(0.148)	(0.105)	(0.096)	(0.089)	(0.077)
GPA 1st Sem.	0.011	0.002	0.002	0.001	0.008
	(0.013)	(0.009)	(0.008)	(0.007)	(0.007)
GPA w/o Math. Rem. 1st Sem.	0.012	0.002	0.002	0.001	0.007
	(0.013)	(0.009)	(0.008)	(0.007)	(0.007)
N	5747	10545	13247	16372	22437
Next Mathematic Course[a]					
Next Mat. Cour. GPA Stand.	0.026	0.003	0.008	0.007	0.014
	(0.019)	(0.012)	(0.011)	(0.010)	(0.009)
Approved Next Math Course	0.005	0.000	0.001	0.001	0.003
	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)
N	4809	8782	11006	13542	18451
Controls	Yes	Yes	Yes	Yes	Yes
Year F. Effect	Yes	Yes	Yes	Yes	Yes
Degree F. Effect	Yes	Yes	Yes	Yes	Yes
Campus F. Effect	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is estimated through independent linear regressions, controlling for the forcing variable centered at cutoff score, cohort, program and campus fixed effects. A dummy indicates if applicant is above the tested threshold. Slope is allowed to vary at each side of the tested threshold. The coefficient indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. Each column consider a different bandwidth.
[a] The "Next Mathematic Course" outcome section only considers the students that did not deserted Duoc UC during the first semester, which means we used a different sample for the estimation. All the balance checks and validation used in the sample for the outcomes sections "Desertion & Graduation" and "Credit Accumulation" have been passed.
Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 4: Estimated Discontinuities in Selected Outcomes

Outcomes	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20	(6) BW=5	(7) BW=10	(8) BW=12.5	(9) BW=15	(10) BW=20
Desertion & Graduation										
Deser. 1st sem.	-0.028†	-0.030**	-0.024*	-0.017*	-0.017*	-0.029†	-0.029**	-0.023*	-0.017†	-0.017*
	(0.014)	(0.010)	(0.009)	(0.008)	(0.007)	(0.014)	(0.010)	(0.009)	(0.008)	(0.007)
Deser. 1st year	-0.012	0.004	-0.001	-0.002	-0.005	-0.012	0.004	-0.001	-0.002	-0.005
	(0.013)	(0.009)	(0.008)	(0.007)	(0.006)	(0.013)	(0.009)	(0.008)	(0.007)	(0.006)
Completed Full Program Coursework	0.025	0.000	0.004	0.003	0.012	0.023	-0.002	0.003	0.002	0.010
	(0.025)	(0.017)	(0.015)	(0.014)	(0.012)	(0.025)	(0.017)	(0.015)	(0.014)	(0.012)
N	5747	10545	13247	16372	22437	5747	10545	13247	16372	22437
Credit Accumulation										
Credits approved 1 sem. (w/o Rem.)	0.498	0.171	0.011	0.066	0.067	0.485	0.148	0.001	0.065	0.053
	(0.415)	(0.287)	(0.257)	(0.236)	(0.203)	(0.415)	(0.286)	(0.256)	(0.235)	(0.202)
Credits approved 2 sem. (w/o Rem.)	1.636†	0.895	0.497	0.470	0.689†	1.599†	0.839	0.454	0.452	0.632
	(0.845)	(0.588)	(0.530)	(0.484)	(0.417)	(0.837)	(0.581)	(0.524)	(0.477)	(0.411)
GPA 1st Sem.	0.153**	0.161***	0.141***	0.134***	0.139***	0.141**	0.159***	0.139***	0.133***	0.132***
	(0.047)	(0.032)	(0.029)	(0.027)	(0.023)	(0.045)	(0.031)	(0.028)	(0.026)	(0.022)
GPA w/o Math. Rem. 1st Sem.	0.048	0.020	-0.005	-0.009	0.001	0.036	0.018	-0.008	-0.010	-0.005
	(0.049)	(0.034)	(0.030)	(0.028)	(0.024)	(0.048)	(0.032)	(0.029)	(0.027)	(0.023)
N	5747	10545	13247	16372	22437	5747	10545	13247	16372	22437
Next Mathematic Course[a]										
Next Mat. Cour. GPA Stand.	0.091	0.066†	0.063†	0.048	0.078**	0.065	0.063†	0.056†	0.042	0.065*
	(0.056)	(0.039)	(0.035)	(0.031)	(0.027)	(0.053)	(0.036)	(0.033)	(0.029)	(0.025)
Apprroved Next Math Course	0.016	-0.006	0.003	0.007	0.016	0.010	-0.007	0.002	0.005	0.014
	(0.027)	(0.018)	(0.016)	(0.015)	(0.013)	(0.026)	(0.018)	(0.016)	(0.014)	(0.012)
N	4809	8782	11006	13542	18451	4809	8782	11006	13542	18451
Controls	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes
Year F. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree F. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Campus F. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is estimated through independent linear regressions, controlling for the forcing variable centered at cutoff score, cohort, program and campus fixed effects. A dummy indicates if applicant is above the tested threshold. Slope is allowed to vary at each side of the tested threshold. The coefficient indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. Each column consider a different subsample, for which we calculated their own optimal bandwidth presented in the last row.

[a] The "Next Mathematic Course" outcome section only considers the students that did not deserted Duoc UC during the first semester, which means we used a different sample for the estimation. All the balance checks and validation used in the sample for the outcomes sections "Desertion & Graduation" and "Credit Accumulation" have been passed.

Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 5: Estimated Discontinuities in Selected Outcomes by Subgroups

Sub Sample (Opt. BW.)	(1) Men (OB:10.5)	(2) Women (OB:10.4)	(3) Day S. (OB:12.5)	(4) Night S. (OB:10.0)	(5) Tec. Dg. (OB:11.9)	(6) Prof. Dg. (OB:9.4)	(7) With MH. (OB:11.0)	(8) Whitout MH. (OB:10.8)
Desertion & Graduation								
Deser. 1st sem.	-0.023*	-0.049*	-0.008	-0.049**	-0.018	-0.043*	-0.022†	-0.038*
	(0.011)	(0.020)	(0.010)	(0.017)	(0.012)	(0.017)	(0.011)	(0.017)
Deser. 1st year	0.009	-0.016	-0.002	0.008	0.001	0.014	-0.004	0.011
	(0.010)	(0.018)	(0.010)	(0.015)	(0.011)	(0.015)	(0.010)	(0.015)
Completed Full Program Coursework	-0.003	-0.001	0.001	0.001	0.009	-0.029	0.006	-0.018
	(0.020)	(0.036)	(0.019)	(0.028)	(0.022)	(0.026)	(0.020)	(0.030)
N	8078	2467	7544	4515	7293	3398	7535	3469
Credit Accumulation & GPA								
Credits approved 1 sem. (w/o Rem.)	-0.012	0.537	-0.582†	0.834†	-0.088	0.324	0.041	0.241
	(0.337)	(0.526)	(0.315)	(0.476)	(0.343)	(0.482)	(0.340)	(0.490)
Credits approved 2 sem. (w/o Rem.)	0.434	2.003†	-0.056	1.467	0.367	1.654†	0.458	1.217
	(0.667)	(1.204)	(0.647)	(0.954)	(0.716)	(0.957)	(0.698)	(0.999)
GPA 1st Sem.	0.165***	0.140*	0.098**	0.207***	0.117**	0.233***	0.142***	0.157**
	(0.037)	(0.056)	(0.035)	(0.052)	(0.037)	(0.055)	(0.037)	(0.056)
GPA w/o Math. Rem. 1st Sem.	0.005	0.057	-0.067†	0.093†	-0.009	0.041	-0.006	0.019
	(0.039)	(0.057)	(0.037)	(0.054)	(0.039)	(0.058)	(0.039)	(0.058)
N	8078	2467	7544	4515	7293	3398	7535	3469
Next Mathematic Course[a]								
Next Mat. Cour. GPA Stand.	0.045	0.084	0.037	0.095	0.064	0.093	0.034	0.120†
	(0.042)	(0.071)	(0.044)	(0.059)	(0.043)	(0.060)	(0.043)	(0.065)
Apprroved Next Math Course	-0.005	-0.036	-0.003	-0.016	0.018	-0.031	-0.014	0.007
	(0.021)	(0.032)	(0.022)	(0.029)	(0.020)	(0.033)	(0.022)	(0.030)
N	6732	2132	6166	3246	6714	2853	6245	2924

Notes: Each coefficient is estimated through independent linear regressions, controlling for the forcing variable centered at cutoff score, cohort, program and campus fixed effects. A dummy indicates if applicant is above the tested threshold. Slope is allowed to vary at each side of the tested threshold. The coefficient indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. Each column consider a different subsample, for which we calculated their own optimal bandwidth presented in the last row.

[a] The "Next Mathematic Course" outcome section only considers the students that did not deserted Duoc UC during the first semester, which means we used a different sample for the estimation. All the balance checks and validation used in the sample for the outcomes sections "Desertion & Graduation" and "Credit Accumulation" have been passed.

Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 6: Estimated Discontinuities in Selected Outcomes (Cohorts 2010 to 2014)

Outcomes	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20	(6) BW=5	(7) BW=10	(8) BW=12.5	(9) BW=15	(10) BW=20
Desertion & Graduation										
Deser. 1st sem.	-0.026	-0.024†	-0.017	-0.013	-0.016†	-0.025	-0.023†	-0.016	-0.012	-0.015
	(0.017)	(0.012)	(0.011)	(0.010)	(0.008)	(0.017)	(0.012)	(0.011)	(0.010)	(0.008)
Deser. 1st year	-0.003	0.010	0.001	-0.005	-0.009	-0.003	0.010	0.001	-0.004	-0.008
	(0.016)	(0.011)	(0.010)	(0.009)	(0.007)	(0.016)	(0.011)	(0.010)	(0.009)	(0.007)
Completed Full Program Coursework	0.034	-0.008	0.013	0.007	0.018	0.029	-0.014	0.008	0.003	0.013
	(0.034)	(0.023)	(0.021)	(0.019)	(0.016)	(0.033)	(0.023)	(0.021)	(0.019)	(0.016)
N	3681	6661	8348	10389	14232	3681	6661	8348	10389	14232
Credit Accumulation & GPA										
Credits approved 1 sem. (w/o Rem.)	0.705	0.245	0.094	0.234	0.129	0.647	0.200	0.064	0.206	0.103
	(0.543)	(0.374)	(0.338)	(0.308)	(0.265)	(0.544)	(0.373)	(0.337)	(0.307)	(0.264)
Credits approved 2 sem. (w/o Rem.)	2.080†	0.958	0.701	0.742	1.099*	1.856†	0.827	0.597	0.629	0.988†
	(1.071)	(0.744)	(0.675)	(0.611)	(0.528)	(1.065)	(0.738)	(0.669)	(0.605)	(0.522)
GPA 1st Sem.	0.179**	0.157***	0.130***	0.135***	0.128***	0.148**	0.142***	0.119***	0.124***	0.117***
	(0.058)	(0.040)	(0.037)	(0.034)	(0.029)	(0.056)	(0.039)	(0.035)	(0.032)	(0.028)
GPA w/o Math. Rem. 1st Sem.	0.096	0.020	-0.020	-0.011	-0.015	0.066	0.006	-0.030	-0.021	-0.026
	(0.060)	(0.041)	(0.038)	(0.034)	(0.030)	(0.058)	(0.040)	(0.036)	(0.033)	(0.029)
N	3681	6661	8348	10389	14232	3681	6661	8348	10389	14232
Next Mathematic Course[a]										
Next Mat. Cour. GPA Stand.	0.172*	0.094†	0.097*	0.072†	0.092**	0.101	0.073	0.080†	0.055	0.075*
	(0.072)	(0.049)	(0.045)	(0.040)	(0.034)	(0.068)	(0.047)	(0.042)	(0.038)	(0.033)
Apprroved Next Math Course	0.034	-0.009	0.009	0.010	0.011	0.015	-0.015	0.004	0.005	0.006
	(0.034)	(0.024)	(0.021)	(0.019)	(0.016)	(0.033)	(0.023)	(0.021)	(0.019)	(0.016)
N	3095	5559	6958	8619	11724	3095	5559	6958	8619	11724
Controls	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes
Year F. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree F. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Campus F. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is estimated through independent linear regressions, controlling for the forcing variable centered at cutoff score, cohort, program and campus fixed effects. A dummy indicates if applicant is above the tested threshold. Slope is allowed to vary at each side of the tested threshold. The coefficient indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. Columns $(1)-(5)$ do not control for any covariable. Columns $(6)-(10)$ include all covariables in the estimation.

[a] The "Next Mathematic Course" outcome section only considers the students that did not deserted Duoc UC during the first semester, which means we used a different sample for the estimation. All the balance checks and validation used in the sample for the outcomes sections "Desertion & Graduation" and "Credit Accumulation" have been passed.

Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 7: Estimated Discontinuities in Selected Outcomes by Subgroups (Cohorts 2010 to 2014)

Sub Sample (Opt. BW.)	(1) Men (OB:11.6)	(2) Women (OB:11.1)	(3) Day S. (OB:14.3)	(4) Night S. (OB:11.2)	(5) Tec. Dg. (OB:12.6)	(6) Prof. Dg. (OB:8.9)	(7) With MH. (OB:11.2)	(8) Whitout MH. (OB:13.1)
Desertion & Graduation								
Deser. 1st sem.	-0.021	-0.019	-0.007	-0.034	-0.002	-0.052*	-0.007	-0.044*
	(0.014)	(0.023)	(0.012)	(0.020)	(0.014)	(0.023)	(0.015)	(0.018)
Deser. 1st year	0.015	-0.027	-0.010	0.020	0.008	-0.004	0.009	-0.021
	(0.012)	(0.022)	(0.011)	(0.017)	(0.013)	(0.020)	(0.013)	(0.017)
Completed Full Program Coursework	0.003	-0.023	-0.007	0.004	0.032	-0.053	-0.008	0.015
	(0.026)	(0.043)	(0.026)	(0.033)	(0.027)	(0.043)	(0.028)	(0.034)
N	5368	1763	5150	3268	5403	1958	4719	3068
Credit Accumulation & GPA								
Credits approved 1 sem. (w/o Rem.)	0.241	-0.222	-0.504	0.800	0.020	0.722	-0.036	0.837
	(0.423)	(0.618)	(0.409)	(0.546)	(0.426)	(0.693)	(0.443)	(0.542)
Credits approved 2 sem. (w/o Rem.)	0.561	1.429	0.317	0.665	0.086	2.794*	-0.083	2.878**
	(0.821)	(1.429)	(0.801)	(1.097)	(0.868)	(1.301)	(0.885)	(1.064)
GPA 1st Sem.	0.148**	0.092	0.093*	0.172**	0.083†	0.255***	0.093*	0.230***
	(0.045)	(0.066)	(0.042)	(0.060)	(0.045)	(0.073)	(0.046)	(0.060)
GPA w/o Math. Rem. 1st Sem.	-0.006	0.002	-0.063	0.035	-0.050	0.107	-0.046	0.080
	(0.046)	(0.067)	(0.043)	(0.062)	(0.045)	(0.076)	(0.047)	(0.062)
N	5368	1763	5150	3268	5403	1958	4719	3068
Next Mathematic Course[a]								
Next Mat. Cour. GPA Stand.	0.081	0.102	0.036	0.084	0.079	0.154*	0.036	0.111
	(0.053)	(0.085)	(0.053)	(0.067)	(0.055)	(0.077)	(0.052)	(0.070)
Apprroved Next Math Course	0.008	-0.051	-0.020	0.004	0.039	-0.050	0.003	0.002
	(0.027)	(0.040)	(0.026)	(0.032)	(0.026)	(0.042)	(0.027)	(0.032)
N	4434	1519	4377	2649	4487	1773	4518	2606

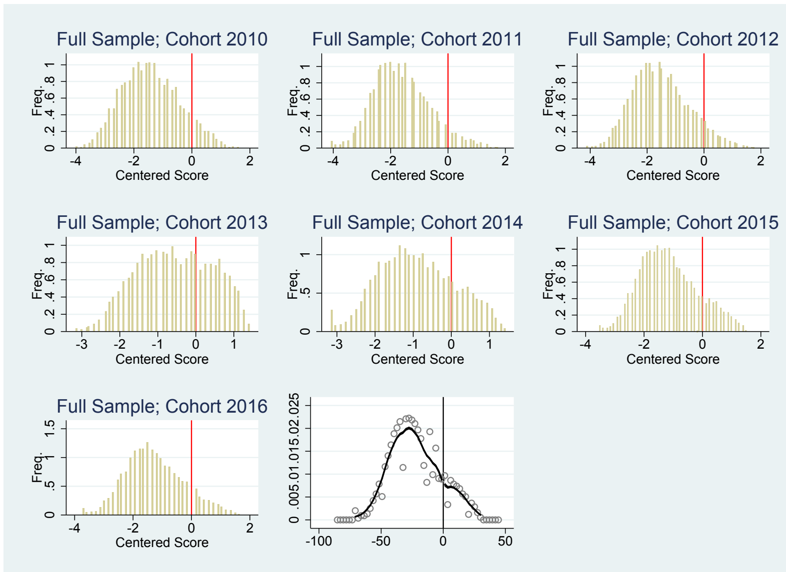
Notes: Each coefficient is estimated through independent linear regressions, controlling for the forcing variable centered at cutoff score, cohort, program and campus fixed effects. A dummy indicates if applicant is above the tested threshold. Slope is allowed to vary at each side of the tested threshold. The coefficient indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. Each column consider a different subsample, for which we calculated their own optimal bandwidth presented in the last row.

[a] The "Next Mathematic Course" outcome section only considers the students that did not deserted Duoc UC during the first semester, which means we used a different sample for the estimation. All the balance checks and validation used in the sample for the outcomes sections "Desertion & Graduation" and "Credit Accumulation" have been passed.

Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

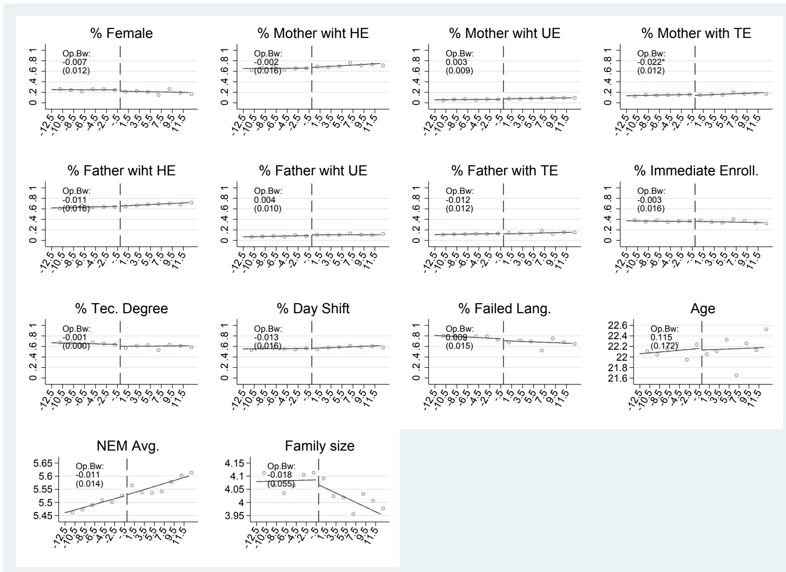
9. Figures

Figure 1: Distribution Checks and McCrary Test



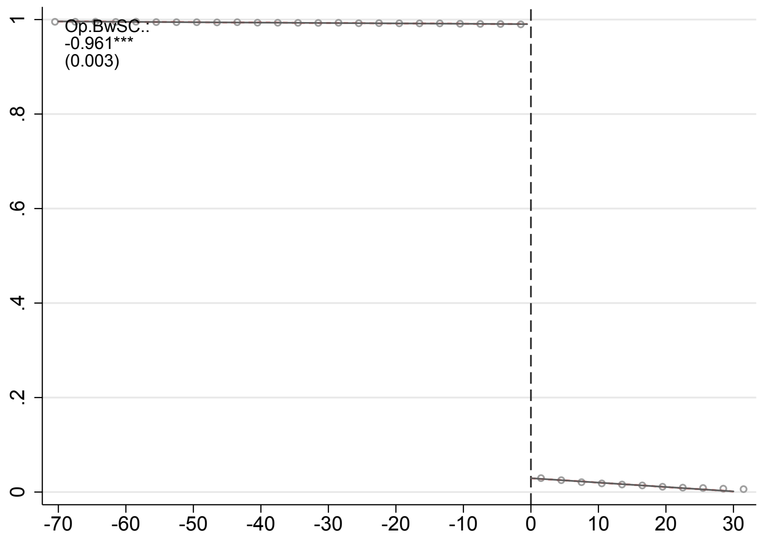
Note. Distribution of Students over diagnostics test score.

Figure 2: Balance Check for Covariables



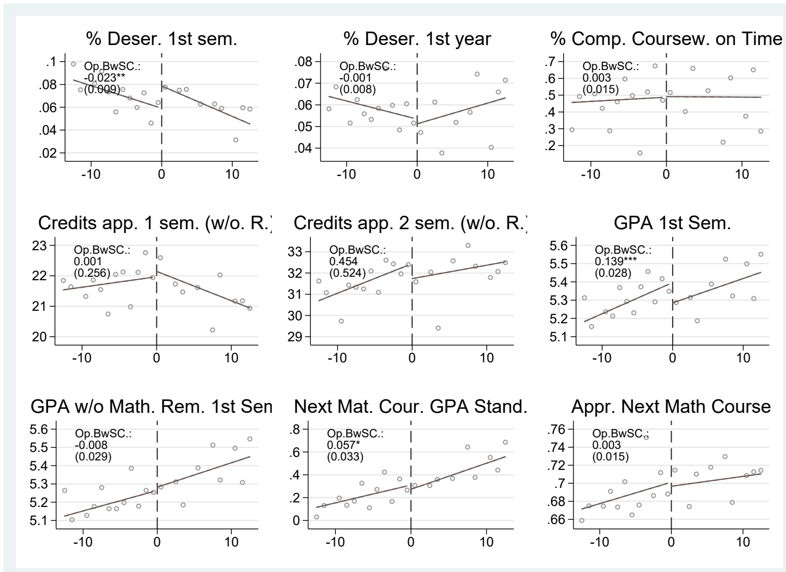
Note. $N = 13247$. Horizontal axis corresponds to the diagnostics test scores centered at the cutoff. Actual values are plotted in bins of size 2. The linear fit represented in solid line uses the CCT optimal bandwidth (12.5). The estimated coefficients of the jump on survey response rate at cutoff score in each model with cohort, general degree and campus fixed effects is presented in the top left area of the graph ("Op. Bw.").

Figure 3: First Stage Results



Note. $N = 54964$. Actual and fitted values for all students. Horizontal axis corresponds to the diagnostics test score centered on the cutoff score. Actual values are plotted in bins of size 3. Coefficients reported in the image are the results of a local regression of the corresponding variable on the centered on the cutoff score, an indicator variable for scoring above the cutoff score and cohort, general degree and campus fixed effects. "Op. Bw." presents the estimate using the optimal bandwidth. Robust standard errors in parenthesis. $*p < 0.1$, $**p < 0.05$, $***p < 0.001$.

Figure 4: Estimated Discontinuities in Selected Outcomes



Note. $N = 13247$. Each figure presents actual and fitted values for all students. Horizontal axis corresponds to the diagnostics test scores centered at the cutoff. Actual values are plotted in bins of size 1. The linear fit represented in solid line uses the CCT optimal bandwidth (12.5). Coefficients reported in the image indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. "Op. Bw." presents the estimate using the optimal bandwidth. Robust standard errors in parenthesis. $*p < 0.1$, $**p < 0.05$, $***p < 0.001$.

Appendix A. Tables

Table A.8: Balance Check for Covariables

Variable	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20
Female	0.030	0.011	0.008	-0.003	0.001
	(0.020)	(0.013)	(0.012)	(0.011)	(0.009)
Mother wiht HE	0.011	-0.006	0.000	-0.002	-0.009
	(0.026)	(0.018)	(0.016)	(0.015)	(0.013)
Mother wiht UE	0.006	0.000	-0.003	-0.002	0.001
	(0.014)	(0.010)	(0.009)	(0.008)	(0.007)
Mother with TE	0.022	0.012	0.022†	0.013	0.005
	(0.020)	(0.014)	(0.012)	(0.011)	(0.010)
Father wiht HE	0.019	0.005	0.013	-0.002	0.000
	(0.027)	(0.018)	(0.016)	(0.015)	(0.013)
Father wiht UE	0.011	0.001	-0.004	-0.005	0.000
	(0.016)	(0.011)	(0.010)	(0.009)	(0.008)
Father with TE	-0.005	0.003	0.012	0.009	-0.001
	(0.019)	(0.013)	(0.012)	(0.010)	(0.009)
Immediate Enroll.	-0.009	0.016	0.001	-0.004	-0.014
	(0.027)	(0.018)	(0.016)	(0.015)	(0.013)
Age	0.313	-0.189	-0.141	-0.053	0.016
	(0.279)	(0.189)	(0.172)	(0.157)	(0.136)
NEM Avg.	0.002	0.007	0.006	0.005	0.014
	(0.023)	(0.015)	(0.014)	(0.013)	(0.011)
Family size	0.024	0.055	0.020	0.007	0.000
	(0.089)	(0.061)	(0.055)	(0.049)	(0.043)
N	5747	10545	13247	16372	22437

Notes: Each coefficient is estimated through independent linear regressions, controlling for the forcing variable centered at cutoff score, cohort, program and campus fixed effects. A dummy indicates if applicant is above the tested threshold. Slope is allowed to vary at each side of the tested threshold. The coefficient indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. Each column consider a different subsample, for which we calculated their own optimal bandwidth presented in the last row.
Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A.9: Estimated Discontinuities in Selected Outcomes - New Model

Outcomes	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20	(6) BW=5	(7) BW=10	(8) BW=12.5	(9) BW=15	(10) BW=20
Desertion & Graduation										
Deser. 1st sem.	-0.021	-0.029**	-0.023*	-0.017†	-0.017*	-0.022	-0.028**	-0.022*	-0.017†	-0.017*
	(0.015)	(0.010)	(0.009)	(0.008)	(0.007)	(0.015)	(0.010)	(0.009)	(0.008)	(0.007)
Deser. 1st year	-0.009	0.003	-0.002	-0.002	-0.005	-0.009	0.004	-0.002	-0.002	-0.005
	(0.014)	(0.009)	(0.008)	(0.007)	(0.006)	(0.014)	(0.009)	(0.008)	(0.007)	(0.006)
Completed Full Program Coursework	0.019	0.005	0.005	0.000	0.010	0.018	0.004	0.004	0.000	0.007
	(0.027)	(0.018)	(0.016)	(0.014)	(0.012)	(0.026)	(0.017)	(0.015)	(0.014)	(0.012)
N	5747	10545	13247	16372	22437	5747	10545	13247	16372	22437
Credit Accumulation										
Credits approved 1 s. (w/o Rem.)	0.346	0.148	0.012	0.085	0.160	0.316	0.127	-0.002	0.086	0.140
	(0.378)	(0.253)	(0.227)	(0.208)	(0.182)	(0.376)	(0.251)	(0.225)	(0.207)	(0.181)
Credits approved 2 s. (w/o Rem.)	1.225	0.807	0.376	0.324	0.618	1.196	0.758	0.334	0.321	0.552
	(0.883)	(0.588)	(0.528)	(0.481)	(0.418)	(0.872)	(0.580)	(0.520)	(0.473)	(0.412)
GPA 1st Sem.	0.122*	0.150***	0.137***	0.129***	0.133***	0.111*	0.148***	0.133***	0.128***	0.125***
	(0.050)	(0.033)	(0.030)	(0.027)	(0.023)	(0.048)	(0.032)	(0.028)	(0.026)	(0.022)
GPA w/o Math. Rem. 1st Sem.	0.018	0.014	-0.007	-0.010	-0.001	0.005	0.012	-0.010	-0.011	-0.009
	(0.052)	(0.035)	(0.031)	(0.028)	(0.024)	(0.050)	(0.033)	(0.030)	(0.027)	(0.023)
N	5747	10545	13247	16372	22437	5747	10545	13247	16372	22437
Next Mathematic Course[a]										
Next Mat. Cour. GPA Stand.	0.083	0.065†	0.060†	0.053†	0.087**	0.056	0.064†	0.052	0.047	0.071**
	(0.061)	(0.039)	(0.035)	(0.032)	(0.027)	(0.057)	(0.037)	(0.033)	(0.030)	(0.026)
Apprroved Next Math Course	0.016	-0.007	0.001	0.005	0.017	0.009	-0.007	-0.001	0.004	0.013
	(0.029)	(0.019)	(0.017)	(0.015)	(0.013)	(0.028)	(0.018)	(0.016)	(0.015)	(0.013)
N	4809	8782	11006	13542	18451	4809	8782	11006	13542	18451
Controls	-	-	-	-	-	Yes	Yes	Yes	Yes	Yes
Year F. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Degree F. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Campus F. Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is estimated through independent linear regressions, controlling for the forcing variable centered at cutoff score, cohort, program and campus fixed effects. A dummy indicates if applicant is above the tested threshold. Slope is allowed to vary at each side of the tested threshold. The coefficient indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. Each column consider a different subsample, for which we calculated their own optimal bandwidth presented in the last row.

[a] The "Next Mathematic Course" outcome section only considers the students that did not deserted Duoc UC during the first semester, which means we used a different sample for the estimation. All the balance checks and validation used in the sample for the outcomes sections "Desertion & Graduation" and "Credit Accumulation" have been passed.

Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A.10: Descriptives for all first-time enrolled Duoc UC students per cohort (Cohorts 2010 to 2014)

Cohorte	Num. Stud.	% Women	%Comp Coursework	%Mother HE	%Tec. Dg.	%Day Shift	%Inm. Enrollment	%Inm. Enrollment
2010	5,893	0.28	0.57	0.60	0.67	0.50	0.82	0.29
2011	4,561	0.31	0.59	0.59	0.67	0.51	0.80	0.40
2012	6,265	0.30	0.58	0.61	0.68	0.50	0.81	0.40
2013	8,642	0.32	0.55	0.62	0.72	0.50	0.90	0.33
2014	8,012	0.30	0.51	0.61	0.75	0.49	0.88	0.34

Notes: HE=High School Education; UE=University Education; TE=Technical Education. NEM is the equivalent in Chile of the GPA in the United States.

Table A.11: Summary Statistics for Covariates among Students (Cohorts 2010 to 2014)

Variables	**Full Sample**			**Below Threshold**			**Above Threshold**			**T-test**
	count	mean	sd	count	mean	sd	count	mean	sd	p
Female	33,367	0.303	0.460	27,814	0.323	0.468	5,553	0.205	0.404	0.000
Mother wiht HE	33,152	0.606	0.489	27,637	0.587	0.492	5,515	0.704	0.456	0.000
Mother wiht UE	33,152	0.052	0.222	27,637	0.043	0.204	5,515	0.096	0.295	0.000
Mother with TE	33,152	0.124	0.330	27,637	0.117	0.321	5,515	0.162	0.368	0.000
Father wiht HE	33,150	0.603	0.489	27,636	0.586	0.493	5,514	0.694	0.461	0.000
Father wiht UE	33,150	0.070	0.255	27,636	0.060	0.237	5,514	0.121	0.326	0.000
Father with TE	33,150	0.113	0.316	27,636	0.107	0.309	5,514	0.141	0.348	0.000
Immediate Enroll.	33,368	0.346	0.476	27,814	0.352	0.478	5,554	0.317	0.466	0.000
Age	33,368	22.470	5.222	27,814	22.445	5.207	5,554	22.597	5.296	0.000
NEM Avg.	33,075	5.444	0.413	27,581	5.412	0.403	5,494	5.605	0.425	0.000
Family size	33,138	4.164	1.574	27,625	4.190	1.587	5,513	4.036	1.502	0.000
Enrolled in Prof. Degree	33,185	0.294	0.455	27,759	0.274	0.446	5,426	0.393	0.488	0.000
Enrolled in Day Shift	33,185	0.500	0.500	27,759	0.488	0.500	5,426	0.560	0.496	0.000
Failed Lang. Diag. Assesment	33,373	0.850	0.357	27,814	0.875	0.331	5,559	0.727	0.446	0.000
Next Math Course	25,857	4.771	1.233	21,142	4.633	1.219	4,715	5.390	1.099	0.000
Passed Next Math Course	33,373	0.631	0.483	27,814	0.616	0.486	5,559	0.707	0.455	0.000
Deser. 1st sem.	33,368	0.108	0.310	27,814	0.117	0.322	5,554	0.059	0.236	0.000
Deser. 1st year	33,368	0.074	0.262	27,814	0.077	0.267	5,554	0.057	0.232	0.000
Credits approved 1st sem.	33,185	34.256	13.946	27,759	33.901	14.375	5,426	36.070	11.330	0.000
Credits approved 1st year	28,778	73.123	23.161	23,760	72.817	23.332	5,018	74.576	22.281	0.000
Completed Coursework	33,368	0.555	0.497	27,814	0.537	0.499	5,554	0.646	0.478	0.000

Notes: HE=High School Education; UE=University Education; TE=Technical Education. NEM is the equivalent in Chile of the GPA in the United States. Last column correspond to a T-test of means between the students that are above and below the threshold for every variable.

Table A.12: Balance Check for Covariables (Cohorts 2010 to 2014)

Variable	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20
Female	0.053*	0.024	0.016	0.004	0.001
	(0.025)	(0.017)	(0.015)	(0.014)	(0.012)
Mother wiht HE	0.017	0.012	0.018	0.001	-0.011
	(0.034)	(0.023)	(0.021)	(0.019)	(0.016)
Mother wiht UE	0.009	0.008	0.006	0.002	0.002
	(0.018)	(0.012)	(0.011)	(0.010)	(0.009)
Mother with TE	0.018	0.015	0.028†	0.023†	0.013
	(0.025)	(0.017)	(0.015)	(0.014)	(0.012)
Father wiht HE	0.039	0.030	0.020	0.000	0.007
	(0.034)	(0.023)	(0.021)	(0.019)	(0.016)
Father wiht UE	0.005	0.010	0.004	-0.001	0.000
	(0.020)	(0.014)	(0.012)	(0.011)	(0.010)
Father with TE	-0.012	-0.010	0.004	0.005	-0.003
	(0.024)	(0.016)	(0.015)	(0.013)	(0.011)
Immediate Enroll.	-0.017	0.013	0.008	0.001	-0.007
	(0.033)	(0.023)	(0.021)	(0.019)	(0.016)
Age	0.536	0.010	-0.046	0.023	0.054
	(0.361)	(0.243)	(0.223)	(0.202)	(0.174)
NEM Avg.	0.029	0.025	0.021	0.023	0.024†
	(0.029)	(0.020)	(0.018)	(0.016)	(0.014)
Family size	0.027	0.048	0.052	0.036	0.026
	(0.113)	(0.078)	(0.071)	(0.063)	(0.054)
N	3681	6661	8348	10389	14232

Notes: Each coefficient is estimated through independent linear regressions, controlling for the forcing variable centered at cutoff score, cohort, program and campus fixed effects. A dummy indicates if applicant is above the tested threshold. Slope is allowed to vary at each side of the tested threshold. The coefficient indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. Each column consider a different subsample, for which we calculated their own optimal bandwidth presented in the last row.
Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A.13: Outcome Balance Index (Cohorts 2010 to 2014)

Outcomes	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20
Desertion & Graduation					
Deser. 1st sem.	-0.001	-0.002	-0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Deser. 1st year	-0.001	0.000	-0.001	-0.001	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Completed Full Program Coursework	0.004	0.005	0.004	0.004	0.005
	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
N	3681	6661	8348	10389	14232
Credit Accumulation					
Credits approved 1 s. (w/o Rem.)	0.014	0.022	0.010	0.002	0.016
	(0.046)	(0.031)	(0.028)	(0.025)	(0.022)
Credits approved 2 s. (w/o Rem.)	0.038	0.056	0.044	0.020	0.064
	(0.148)	(0.105)	(0.096)	(0.089)	(0.077)
GPA 1st Sem.	0.011	0.002	0.002	0.001	0.008
	(0.013)	(0.009)	(0.008)	(0.007)	(0.007)
GPA w/o Math. Rem. 1st Sem.	0.012	0.002	0.002	0.001	0.007
	(0.013)	(0.009)	(0.008)	(0.007)	(0.007)
N	5747	10545	13247	16372	22437
Next Mathematic Course					
Next Mat. Cour. GPA Stand.	0.071**	0.022	0.018	0.018	0.019†
	(0.024)	(0.015)	(0.014)	(0.012)	(0.011)
Apprroved Next Math Course	0.019**	0.006	0.004	0.005	0.005
	(0.007)	(0.004)	(0.004)	(0.004)	(0.003)
N	3095	5559	6958	8619	11724
Controls	Yes	Yes	Yes	Yes	Yes
Year F. Effect	Yes	Yes	Yes	Yes	Yes
Degree F. Effect	Yes	Yes	Yes	Yes	Yes
Campus F. Effect	Yes	Yes	Yes	Yes	Yes

Notes: Each coefficient is estimated through independent linear regressions, controlling for the forcing variable centered at cutoff score, cohort, program and campus fixed effects. A dummy indicates if applicant is above the tested threshold. Slope is allowed to vary at each side of the tested threshold. The coefficient indicates the estimated jump at the corresponding threshold, i.e. the jump for students who are above the math test threshold and did not need to take the remedial course. Each column consider a different bandwidth.
Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.