The Effects of Remedial Math on Student Outcomes: Evidence from an Open-Access 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 remedial courses for academically underprepared students is an essential endeavor. Remedial courses provide opportunities to students who might not otherwise succeed in college-level work to enter in higher education and develop an important skill set in their initial semester of enrollment. In this way, remedial courses provide access to students whose earlier academic experiences might otherwise have been a barrier to entry. However, for all of the potential benefits of college remediation, additional required coursework may increase students' financial and academic burden and may contribute to drop out. To date, much of the research on the effects of college remedial coursework has been focused in the United States. Our study takes advantage of a unique administrative dataset to examine the effects of enrollment in remedial courses on student outcomes in an international context.

Using data on students attending one of the largest vocational education postsecondary institutions in Chile, we attempt to isolate the effects of taking an additional semester-long remedial course in the first semester on subsequent grades in college-level math by comparing students who were required to take the course to those who just barely passed the placement exam and, thus, did not have to enroll in corequisite remediation. Exploiting an institutional cutoff score on the placement examination used to assign students to remedial math courses, we employ a Regression Discontinuity (RD) research design to provide causal estimates of the effects of the remedial courses on the subsequent academic outcomes of students placed in math remediation. However, unlike prior research, we have the particular advantage that all students in our sample take the same courses at the same time, 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 little variation within majors in the courses students take in the Chilean campus in our study. We focus on the effects of taking a remedial math course in the first semester on grades in the next college-level math course, and student persistence to the second year. We ask the following question: Does participation in a remedial math course improve course performance in the next course for students at the margins of passing the placement test?

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

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1. Introduction

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. In the pursuit for equity in both the United States and in other countries, it is essential to understand the impact of different models of remedial education on student outcomes. These courses are typically the gateway by which academically underprepared students begin their postsecondary study. The two most common remedial subjects are Math and Writing. While writing skills are obviously fundamental to students later academic success, math skills can be equally as important given the minimum math requirements of most college degree programs and the low-level of math skills among many entering students. In this way, remedial math courses can serve as a key barrier to students later academic success, particularly in technical programs such as engineering and other science majors.

The vast number of students entering college who are academically unprepared for college-level work has created a strain on postsecondary institutions and the students they enroll. Current estimates suggest that half of all undergraduates and 70 percent of community college students in the United

States take at least one remedial course while in college. (National Center for Education Statistics[1], 2003; Bailey, 2009; Scott-Clayton & Rodriguez, 2012). Community colleges disproportionately serve students who require remediation to develop their skills in one or more areas. In the United States, funding mechanisms for community colleges Evidence suggesting the efficacy of corequisite remediation has increased the popularity of this model, however institutions and systems must consider the increased the popularity of this model, but also the increased costs associated with implementing such a model. While early evidence suggests a corequisite remedial model is cost effective (Belfield et al., 2016), there is not clear evidence of the effects of remediation student outcomes.

The challenges inherent in educating large numbers of academically underprepared students have resulted in a rapidly growing body of research on the effects of remedial college courses on student outcomes. Prior research in U.S. colleges has yielded inconclusive evidence of the effects of remediation on student success. Edgecombe et al. (2013), Martorell & McFralin (2011) and Bettinger & Long (2009) show some positive results on various student achievement outcomes, while Duchini (2017), Boatman & Long (2010) and Scott-Clayton & Rodriguez (2015) show either negative or non-significant effects of the remedial courses. These inconsistent results have resulted in controversy over the provision and format of remedial coursework due to concerns that remediation presents obstacles in the way of students success and may contribute to a "cooling out" of postsecondary aspirations (Bailey et al., 2010; Deil-Amen & Rosenbaum, 2002). Recent qualitative evidence suggests the importance of both format and pedagogy (Wang, Sun, & Wickersham, 2017; Boatman & Kramer, 2018). However, isolating the effects of taking a remedial course has been difficult to study in the U.S. due to selection bias and ambiguously or inconsistently defined placement policies. We do not yet have a clear picture as to whether or not taking a remedial course in college actually results in better outcomes in subsequent college courses or yields better degree attainment.

This study examines the effects of enrolling in a remedial math class among students attending one of the largest Vocational Education and Train-

[1] NCES

ing institutions in Chile. As such, we add to the current research on the effect of remedial education in an international context and within a non-flexible academic program, allowing us to isolate the effects of these courses on student grades in college. The results from this analysis provide insight into the extent to which a remedial model that does not lengthen the time to degree has a potentially positive impact on students subsequent academic success in later math courses.

Chile is a well-suited site to study the effects of remediation on subsequent math achievement for several reasons. As Chiles economy has developed, demand for service labor, which is predominantly knowledge-based, has increased compared to manufacturing labor, which is more physically-based. Driven largely by technological developments, this shift toward service labor has led to an increased demand for educated workers. Labor market changes like this one are likely to continue as a result of economic development, increasing the returns to education and the importance of greater participation in postsecondary education (Ministry of Finance of Chile, 2013; Gallego, 2012). The Ministry of Education of Chile, with support from the World Bank, has recently created quality enhancement programs that provide grants to postsecondary institutions to improve basic skills remediation for students (Ministry of Education of Chile, 2012). Although Chiles PISA scores improved between 2000 and 2009, the country still ranked below the OECD average in reading, science, and math in 2009.

2. Related Literature (in construction)

Results from this paper contributes to the growing literature that studies the effects of remedial courses[2] on student outcomes. First, we present results that are free from key methodological and data limitations faced by earlier studies. O'Hear & MacDonald (1995) were not able to account for the differences between the treated and the control group of students. Bettinger & Long (2009) use an IV strategy that uses the different remediation programs across colleges in Ohio but are limited in their ability to account for the ways in which students from different colleges may differ along dimensions

[2] Also known as developmental education.

other than the remediation policies to which they exposed. 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.

This paper contibutes 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 on the basis of 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. Boatman & Long (2018) study the effect of remedial courses on college students with different levels of academic preparedness. Through an RD design, they found negative effects on students retention and no effect on math course completion. However, when they consider student with lower levels of academic preparation, they estimate positive, statistically significant effects of remediation (Boatman & Long, 2018).

On the other hand Duchini (2017) fails to find any positive or significant results of a remedial program for an undergraduate economics program on a university in Italy. Scott-Clayton & Rodriguez (2015) results, similarly to Martorell & McFarlin (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 this remedial courses tend to have an 8 percentage point increase in the probability of dropping out from college. Valentine et al. (2017) provides 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 large magnitude of the different remedial programs in the likelihood to pass following math courses, the amounts of credits passed and other academic attainments.

Finally, the paper expands the existing body of literature on remedial studies 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 a very specific subset of the undergraduate population in Chile and the remediation program was not particularly well defined. The study sample included 21 dental students who had been flagged for remediation after receiving a grade below sufficient on at least one of three exams in their course of study. These students were then exposed to "seminars, case-based learning and problem-based learning, directed study, plenary discussions and debate, integration and questions, and web-based learning" so that students could benefit from the one that best aligned with their unique learning style. The students were tested again after the interventions. Mean grades among those 21 students had improved and were in fact higher than the students who did not receive the interventions (Alcota, Muoz, & Gonzlez, 2011, p. 1390).

In a descriptive study in 2005, Duoc UC observed that students who completed the remedial Math 100 course received a final grade of 5.4 ($Sd = 0.83$) in their next mathematical course, while those who already demonstrated sufficient math level and were exempted from the remedial course earned a 5.5 ($Sd = 1.27$). While this is not an appropriate comparison given the different initial levels of each group, their average final grades were not significantly different, suggesting that remedial Math 100 had positive effects on the later academic success of the participants.

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 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 [3]. 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 & Mogolln, 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). The diversification of institutions presented more opportunities for low-income students. Enrollment of students in the two lowest income quintiles 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 postsecondary levels (Crawford & Mogolln, 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[4]. Duoc UC cur-

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

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

rently 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.

4. Remedial Courses

Due to Duoc UC's open admissions policy across all its campuses, the college 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 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.

Duoc UC's math remediation model 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 a 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 math course (for example Algebra or Math 200). All students in remedial Math 100 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 remedial Math 100 can retake the course during the second semester.

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 [5]. Students who skip the test are automatically registered in the remedial class[6]. 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.

Given the structure of the remedial courses in Chile, 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 Chile. 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?

5. Empirical 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.

[5]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.

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

Simply contrasting the average outcomes of these two different groups[7] ignores the problem of selection and tells us nothing about whether differences in student outcomes were actually 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 a rigorous non-biased estimation of the impact of being registered for remedial courses (Shadish et al., 2002; Murnane & Willett, 2011).

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.

It is possible that being assigned to remedial coursework has short-, medium-, and long-term outcomes. Thus, we examine if the effects of enrolling in remedial math at Duoc UC do...

1. increase students likelihood to pass their next college-level math course?
2. increase students performance in their next college-level math course?
3. increase students retention rates?
4. increase students likelihood to complete their full coursework?

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

5.1. 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, etc.); (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.

With these data sources we obtain a longitudinal dataset that allows us to follow the academic progress of every student that enrolled[9] in Duoc UC between 2010 and 2016.

5.2. Students' outcomes

The most proximal outcomes that we consider in this study are tied 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: (1) grades in the next math course; (2) the likelihood of getting a passing grade in the next math course; (3) drop out during the first semester; (4) drop out during the first year. The first and second outcome, subsequent course grade and the likelihood of passing the course, are very closely tied to the purpose of remediation: development of subject-area skill. The sole purpose of remedial coursework, as mentioned before, 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) in most of the degrees considered in

[8] Private, Subsidized and public.

[9] In Duoc UC some students begin their degrees with some courses already validated from their studies in other institutions. This kind of students were not consider in this study.

this study.

It is important also to consider outcomes related to student persistence. The design of the remedial course results in a greater workload for lower-skilled students. It is possible that this course schedule could overwhelm them and force them to leave their degree program and the institution itself. We consider both drop out during the semester of enrollment in remedial math, as well as drop out during the first year in order to account for student persistence during and after remedial math enrollment.

5.3. Sample

As a first step in our analysis, we define the main analytical sample of this study 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. We only consider students from the Business & Administration, Engineering and Informatics & Telecommunications departments. Duoc UC is one of the largest Vocational Education and Training institutions in Chile (see Table 1 for the total of student's in each campus in Duoc UC) and represents a large number of middle and low-income students. In this study, our main sample size is 54.971 students. Table 1 describres the population by cohort. While the size seems to duplicate in 5 years, the characteristics of cohorts are 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 bellow 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[10]. Additional to the main analytical sample we created a sample of those students with available long term outcomes as next math course grade and completed course work. In this sample we consider

[10] "Notas de Enseanza Media", which translate to Grades from High school.

only students who started the second semester in Duoc UC.

[**Table 2**]

5.4. Outcomes

Furthermore, in this study we consider two different groups of outcomes. The first group are consider the short-term outcomes, where every student in the sample has data for every outcome: (1) drop out during their first undergraduate semester; (2) drop out during their first undergraduate year; (3) completion of their full coursework; (4) amount of credits passed from the total taken during their 1st semester; (5) percentage of credits passed from the total taken during the first semester.

The second group of outcomes are consider as the mid and long-term outcomes, where only the students that didn't drop out during the first semester in Duoc UC: (1)next math course grade; (2) the likelihood of getting a passing grade in the next math course; (3) the likelihood of completing the coursework; (4) the number of credits passed during the first semester; (5) the number of credits passed during the first year; (6) percentage of credits passed from the credits taken during the first semester; (7) percentage of credits passed from the credits taken during the first year; (8) percentage of credits passed from the total required by the degree during the first semester; (9) percentage of credits passed from the total required by degree during the first year; (10) amount of credits assigned by the program for the first semester but taken by the student during the second semester.

6. Analytical Strategy

The main focus of this study is to obtain the causal effects of the remedial math course placement on student outcomes. We can not just compare students that failed their diagnostic test and had to take the remedial course with the students who pass it because the characteristics of the students in the two groups can be very different, which would bias the effect's estimation.

To mitigate bias, we adopt a design very similar to the one used in the papers of Lee & Lemieux (2010), which takes advantage of the institutional cutoff score on the diagnostics math test. So, by considering the students' just above and just below this cutoff score, it is possible to assume that the two groups are similar in both observable and unobservable characteristics (Lee & Lemieux, 2010).

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

$$\begin{aligned} y_{ijkh} = \beta_0 + \beta_{1j} S_{ijkh} + \beta_2 C_{ijkh} + \beta_3 C_{ijkh} * S_{ijkh} + \beta_4 Z_{ijkh} + cohort_j \\ + degree_k + campus_h + \epsilon_{ijkh} \end{aligned} \tag{1}$$

Where 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 above or equal to 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 causal effect of the take-up of remediation on outcome, y_{ijkh} for the i^{th} student of the j^{th} cohort and the k^{th} general degree, and where the 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 (2010). First, we need to ensure that the diagnostic test score is not influenced by the treatment. This condition is met because 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 ignorably randomly around the cutoff. This ensure us that the students that failed the diagnostic test are not systematically different from the ones that passed. We test for violations of this 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 assigns 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 showed us.

[**Figure 1**]

We also 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. Table 4 repeats the same process considering different bandwidths.

[**Figure 2**]

Among 132 models that tested 11 covariates, we find that only two models 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 two different models.

[**Table 4**]

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,

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

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 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, 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". Figure 5 plots this index against the running variable. The estimates for all the subsamples considered can be seen in Table A.20 and A.21.

[**Figure 5**]

[**Table A.20**]

[**Table A.21**]

6.1. First Stage

In order to appropriately run our models, we have to determine whetever the discontinuity presented in the data is "Fuzzy" or "Sharp". 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. But 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. In addition, there are other students who 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 6 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 this is a "Sharp" discontinuity.

[**Figure 6**]

7. Results

We now present the results of our main regression, where we estimate the effect of the remedial math course in 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 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 persistence and attainment. We also believe that the students who were forced to take the remedial course, will have higher grades for their mathematical courses, a lower rate of drop out during their first semester and first year.

The impact that this remedial math course may have on the four main students' outcomes does not only depend on the students and on the topics that are taught, but also on the burden of taking an additional course during the first semester.

The biggest estimated differences in the outcomes between the two groups of students near the cutoff are in the next math course grade, drop out rate during the first semester and the amount of credits approved during the first semester. By contrast, all the difference in the long term outcomes, including graduation rate, on time graduation rate, drop out rate during the first year and amount of credits passed during the first year, are not statistically significant.

Taking this into account, the results in Table 5 show us that the students who barely failed the diagnostics test, drop out 2.4% less than the ones who passed the diagnostics test. Also, the student who where forced to take the remedial course rated their teachers on average (not considering the students rating of the teacher in the remedial courses) with a lower quality than the control group. But when we include students rating of the teacher in the remedial courses (outcome "Stud. rating of teach. w. remedial"), this difference disappears, which points to the possibility that the students view their teachers from the remedial courses as very good teachers and thus, they raise the bar for all other teachers.

In Table 5 we also see that the students from the remedial course accumulated fewer credits that the other students who passed the diagnostics test. At first glance, this points to the possibility that the remedial course is a burden on the students and may lower their grades in the rest of their courses.

It is important to note that these results show that the students who barely failed the diagnostic test passed only 0.872 credits fewer than the ones that barely passed it, where the minimum amount of credits that a courses possesses is 4 credits. For the percentage of credits from the total taken during the first semester the results show a very similar scenario. Students that took the remedial course only passed 0.008% less than the ones who skip it, but this result is not statistically significant.

Table 6 shows that stundets in the remedial course managed to get, on average, 0.080 points more than the students that didn't took the course, in the final grade for their next math course. 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. Sadly though, there are no statistically significant effects in the likelihood of the student getting a passing grade in the next math course.

[**Table 5**]

[**Table 6**]

Next we present the results in Tables 7 and 8, where we explore the heterogenety of the results. From columns (1)-(8) we present the estimation results for the same model as in tables 5 and 6, but considering different sub-samples of students: (1) Only male students; (2) Only female students; (3) Students from the day shift program; (4) Students from the night shift program; (5) Students who enrolled in a technical degree; (6) Students who enrolled in a profesional degree; (7) Students whose mothers have highschool education; (8) Students whose mothers do not have highschool education. We calculated a new optimal bandwidth for each subgroup, which are all reported at the end of Tables 7 and 8

In column (1) we can see that men who took the remedial course have a lower drop out rate and fewer passed credits during their first semester, in comparison with those exempt to take the course. In column (2) we see that women who took the remedial course have a lower rate of drop out during the first semester and first year, in comparison with those who where exempt to take the course.

The negative effect on credit accumulation still remains for columns (1), (3), (5) y (7), which indicates a very stable effect. But in regards with the other outcomes, we can see that most of them loss their statistical significance, which points to the fact that there is no heterogenity in our results.

[**Table 7**]

[**Table 8**]

7.1. Confirmation Test

Because the professional degree programs require a minimum of four years of enrollment, we excluded the completed coursework from the initial estimation. Thus, in this section we only consider the cohorts where all students had the opportunity to finish the coursework. By doing so, we seek to estimate unbiased results of the effect of remedial math placement on completed coursework and to confirm our previously estimated results. The balance checks largely show the same results as our previous specifications, with the exception of three models. However, the balance check for the outcome index confirms that the are no statistically significant differences in the characteristics of students who just barely failed the diagnostic test and those who barely passed it (All results can be viewed in Tables A.11-A.20).

The results in the appendix Tables 18 and 19 show the same trend as the main results, however fewer specifications yield statistically significant effect estimates. The magnitude of the estimated effects also is diminished. The remedial courses seem to have a significant effect in the likelihood of the students to complete their coursework in specifications (5) and (6) of the second sample of outcomes. In the case of technical degrees enrolles, treatment increases the likelihood of completing the coursework by 5.6 percentage points. For professional degree-seeking students, treatment seems to lower the likelihood by 12.8 percentage points.

[**Table 18**]

[**Table 19**]

8. Conclusion

Remedial education has been a growing feature of education at higher education institutions around the world. The current literature has primarily estimated the effects of remedial education on students in colleges in the United States. Our paper contributes to prior evidence from various studies on the effects of student placement in remedial courses by estimating the effects of being just below the cutoff score on short-, medium-, and long-term outcomes 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, such as next math course grades. However, there is suggestive evidence that the burden of additional coursework may negatively affect student performance.

We examine the particular remedial program implemented at Duoc UC in order to avoid various limitations presented in former studies such as O'Hear & MacDonald (1995) or Jepsen (2006). In this remedial program, every new student is forced to take a placement and if the student scores below 70 points, they must take a remedial math course. This course is the same for every degree program consider in this study. Moreover, our analysis includes different subsamples which allowed us to verify if different groups of students respond to the treatment in different ways. For the most part, the result do not tend to change across the different subsamples.

The results from our analysis shows that this remedial program does have a positive and significant effect in improving the students' next math course grades in average by 0.080 points, above the grades from student who did no take the remedial course. But it had no statistically significant effect in the likelihood of passing the next math course. Also, we find positive results in the drop out rate of the first semester, but no so for the drop rate of the first year. However, our estimation results also show signs that this remedial program is exhausting the students who failed the placement exam. These students that barely failed the exam, passed 0.775 credits fewer than the ones that barely passed it.

Our analysis suggests that the effects are in fact positive in aiding the students to catch up with their classmates, thus achieving the whole purpose, at least at an institutional level, of this remedial program. But it also shows that the fact of adding an extra course to do so, is exhausting them up to the point that they fail in a very small fraction of their other courses.

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10. Tables

Table 1: General Table

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: Balance Characteristics - Main Analytical Sample

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 4: Balance Characteristics - Persistance Sample

Variable	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20
Female	0.024	0.010	0.006	-0.003	0.004
	(0.022)	(0.015)	(0.013)	(0.012)	(0.010)
Mother wiht HE	0.005	-0.001	0.003	-0.002	-0.009
	(0.029)	(0.020)	(0.018)	(0.016)	(0.014)
Mother wiht UE	0.014	0.007	0.003	0.004	0.009
	(0.015)	(0.011)	(0.009)	(0.009)	(0.007)
Mother with TE	0.014	0.010	0.020	0.007	0.001
	(0.023)	(0.015)	(0.014)	(0.012)	(0.011)
Father wiht HE	0.007	0.007	0.020	0.000	-0.003
	(0.029)	(0.020)	(0.018)	(0.016)	(0.014)
Father wiht UE	0.024	0.011	0.008	0.004	0.006
	(0.018)	(0.012)	(0.011)	(0.010)	(0.008)
Father with TE	-0.012	0.005	0.014	0.011	0.001
	(0.021)	(0.014)	(0.013)	(0.011)	(0.010)
Immediate Enroll.	-0.020	0.011	-0.002	-0.006	-0.019
	(0.029)	(0.020)	(0.018)	(0.016)	(0.014)
Age	0.397	-0.073	-0.040	0.014	0.079
	(0.302)	(0.206)	(0.188)	(0.171)	(0.149)
NEM Avg.	0.017	0.005	0.011	0.011	0.017
	(0.025)	(0.017)	(0.015)	(0.014)	(0.012)
Family size	0.047	0.063	0.042	0.042	0.028
	(0.096)	(0.066)	(0.059)	(0.054)	(0.046)
N	4809	8782	11006	13542	18452

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 5: Results from RD effect of Remedial Course - Main Sample

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
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)
Student rating of teachers	-1.216	-0.910	-0.831†	-0.343	-0.232	-1.198	-0.937†	-0.845†	-0.341	-0.233
	(0.834)	(0.560)	(0.491)	(0.451)	(0.385)	(0.834)	(0.560)	(0.491)	(0.451)	(0.385)
Stud. rating of teach. (w. rem.)	-0.334	-0.277	-0.223	0.273	0.393	-0.313	-0.289	-0.230	0.277	0.390
	(0.824)	(0.559)	(0.490)	(0.451)	(0.385)	(0.823)	(0.558)	(0.489)	(0.451)	(0.385)
Credit appr. 1st sem.	-0.332	-0.655†	-0.861**	-0.825**	-0.812**	-0.335	-0.689*	-0.872**	-0.826**	-0.825***
	(0.508)	(0.349)	(0.313)	(0.286)	(0.247)	(0.507)	(0.348)	(0.311)	(0.284)	(0.246)
% Cred. Appr. 1st Sem.	0.001	-0.002	-0.008	-0.009	-0.007	0.000	-0.003	-0.008	-0.009	-0.008
	(0.010)	(0.007)	(0.006)	(0.005)	(0.005)	(0.010)	(0.007)	(0.006)	(0.005)	(0.005)
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
N	5747	10545	13247	16372	22437	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. Columns (1) − (5) do not control for any covariable. Columns (6) − (10) include all covariables in the estimation.
Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 6: Results from RD effect of Remedial Course - Persistent Sample

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
Next Math Course	0.115	0.084†	0.080†	0.061	0.101**	0.082	0.080†	0.071†	0.053	0.085**
	(0.071)	(0.049)	(0.044)	(0.039)	(0.034)	(0.067)	(0.046)	(0.041)	(0.037)	(0.032)
Appr. Next Math Course	0.016	-0.006	0.003	0.007	0.017	0.010	-0.007	0.002	0.006	0.014
	(0.027)	(0.018)	(0.016)	(0.015)	(0.013)	(0.026)	(0.018)	(0.016)	(0.014)	(0.012)
Deser. 1st year	-0.003	0.001	-0.003	-0.001	-0.004	-0.003	0.001	-0.003	-0.001	-0.004
	(0.011)	(0.007)	(0.006)	(0.006)	(0.005)	(0.011)	(0.007)	(0.006)	(0.006)	(0.005)
Completed Coursework	0.011	-0.006	0.003	0.003	0.007	0.007	-0.007	0.001	0.002	0.005
	(0.026)	(0.018)	(0.016)	(0.015)	(0.013)	(0.026)	(0.018)	(0.016)	(0.015)	(0.013)
Credit appr. 1st sem.	-0.260	-0.734**	-0.664**	-0.577**	-0.689***	-0.253	-0.736**	-0.655**	-0.573**	-0.687***
	(0.380)	(0.259)	(0.230)	(0.210)	(0.180)	(0.381)	(0.259)	(0.230)	(0.210)	(0.179)
Credit appr. 1st year	0.236	-0.971†	-0.919†	-0.696	-0.588	0.169	-0.967†	-0.922†	-0.710	-0.633†
	(0.798)	(0.554)	(0.492)	(0.447)	(0.385)	(0.793)	(0.550)	(0.488)	(0.443)	(0.382)
% Cred. Appr. 1st Sem.	0.006	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000	0.000
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
% Cred. Appr. 1st Year	0.007	-0.003	-0.002	-0.001	0.003	0.005	-0.003	-0.003	-0.002	0.002
	(0.007)	(0.004)	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
% Cred. Appr. 1st Sem. from Total	-0.002	-0.003**	-0.003*	-0.002*	-0.003***	-0.002	-0.003**	-0.003*	-0.002*	-0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
% Cred. Appr. 1st Year from Total	0.000	-0.003	-0.003	-0.002	-0.002	0.000	-0.003	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Cred. of 1st Sem. in 2nd Sem.	-0.151*	-0.072	-0.022	-0.013	0.011	-0.147*	-0.071	-0.022	-0.012	0.013
	(0.065)	(0.047)	(0.040)	(0.037)	(0.032)	(0.064)	(0.046)	(0.040)	(0.036)	(0.031)
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
N	4809	8782	11006	13542	18452	4809	8782	11006	13542	18452

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

Table 7: Results Summary by Subgroups in Main Sample

Sub Sample	(1) Men	(2) Women	(3) Day S.	(4) Night S.	(5) Tec. Dg.	(6) Prof. Dg.	(7) With MH.	(8) Whitout MH.
Deser. 1st sem.	-0.023*	-0.049*	-0.008	-0.040*	-0.018	-0.043*	-0.022†	-0.038*
	(0.011)	(0.020)	(0.010)	(0.019)	(0.012)	(0.017)	(0.011)	(0.017)
Deser. 1st year	0.010	-0.016	-0.002	0.005	0.001	0.014	-0.004	0.011
	(0.010)	(0.018)	(0.010)	(0.016)	(0.011)	(0.015)	(0.010)	(0.015)
Student rating of teachers	-1.171†	0.137	-0.479	-1.077	-1.481*	0.359	-0.464	-1.756†
	(0.663)	(1.020)	(0.631)	(0.885)	(0.670)	(0.932)	(0.663)	(0.975)
Stud. rating of teach. (w. remedial)	-0.130	-0.649	-0.196	0.415	-0.834	1.344	0.010	-0.670
	(0.647)	(1.108)	(0.639)	(0.879)	(0.677)	(0.912)	(0.659)	(0.971)
Credit appr. 1st sem.	-0.784†	-0.553	-1.555***	0.005	-0.707†	-0.691	-0.777†	-0.639
	(0.409)	(0.661)	(0.384)	(0.608)	(0.421)	(0.587)	(0.418)	(0.597)
% Cred. Appr. 1st Sem.	-0.007	0.011	-0.020*	0.007	-0.005	0.006	-0.004	-0.005
	(0.008)	(0.012)	(0.007)	(0.012)	(0.008)	(0.012)	(0.008)	(0.012)
N	8078	2467	7544	4039	7293	3398	7535	3469
Opt. Bw.	10.4	10.4	12.6	9.9	11.8	9.0	11.0	10.8

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 8: Results Summary by Subgroups in Persistent Sample

Sub Sample	(1) Men	(2) Women	(3) Day S.	(4) Night S.	(5) Tec. Dg.	(6) Prof. Dg.	(7) With MH.	(8) Whitout MH.
Next Math Course	0.070	0.105	0.058	0.119	0.079	0.145†	0.044	0.145†
	(0.053)	(0.089)	(0.054)	(0.074)	(0.054)	(0.078)	(0.055)	(0.082)
Appr. Next Math Course	0.000	-0.036	0.000	-0.016	0.018	-0.024	-0.015	0.007
	(0.021)	(0.032)	(0.021)	(0.029)	(0.020)	(0.034)	(0.022)	(0.030)
Deser. 1st year	0.014	-0.042**	-0.004	0.000	-0.007	0.004	-0.002	-0.003
	(0.009)	(0.013)	(0.007)	(0.014)	(0.009)	(0.012)	(0.008)	(0.014)
% Cred. Appr. 1st Sem.	-0.002	0.005	-0.003	0.004	0.001	0.006	-0.003	0.006
	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)
% Cred. Appr. 1st Year	-0.006	0.006	-0.003	-0.005	0.001	0.006	-0.007	0.004
	(0.005)	(0.008)	(0.005)	(0.007)	(0.005)	(0.008)	(0.005)	(0.008)
% Cred. Appr. 1st Sem. from Total	-0.003*	-0.004*	-0.004**	-0.001	-0.002	-0.002†	-0.004**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% Cred. Appr. 1st Year from Total	-0.004	-0.002	-0.004†	-0.001	-0.003	-0.001	-0.006*	0.001
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Cred. of 1st Sem. in 2nd Sem.	-0.082	-0.051	-0.050	-0.011	-0.037	-0.099	-0.052	-0.090
	(0.056)	(0.081)	(0.063)	(0.034)	(0.045)	(0.089)	(0.053)	(0.078)
N	6650	2132	6436	3246	6714	2725	6245	2924
Opt. Bw.	10.5	10.4	12.5	9.6	12.1	8.9	11.1	10.8

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 9: Descriptives for all first-time enrolled Duoc UC students per cohort (2010-2014)

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 10: Summary Statistics for Covariates among Students (2010-2014)

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 11: Balance Characteristics - Sample 1 (2010-2014)

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 12: Balance Characteristics - Sample 2 (2010-2014)

Variable	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20
Female	0.048†	0.017	0.009	-0.002	-0.001
	(0.028)	(0.019)	(0.017)	(0.015)	(0.013)
Mother wiht HE	-0.007	0.004	0.005	-0.011	-0.020
	(0.037)	(0.025)	(0.023)	(0.021)	(0.018)
Mother wiht UE	0.020	0.017	0.011	0.005	0.006
	(0.019)	(0.013)	(0.012)	(0.011)	(0.009)
Mother with TE	-0.004	0.006	0.022	0.010	0.005
	(0.027)	(0.019)	(0.017)	(0.015)	(0.013)
Father wiht HE	0.021	0.031	0.022	0.003	0.000
	(0.037)	(0.025)	(0.023)	(0.021)	(0.018)
Father wiht UE	0.016	0.018	0.015	0.007	0.007
	(0.022)	(0.015)	(0.013)	(0.012)	(0.010)
Father with TE	-0.028	-0.013	0.003	0.007	0.000
	(0.026)	(0.018)	(0.016)	(0.015)	(0.013)
Immediate Enroll.	-0.020	0.014	0.008	0.001	-0.013
	(0.037)	(0.025)	(0.023)	(0.021)	(0.018)
Age	0.783*	0.088	0.047	0.103	0.144
	(0.390)	(0.263)	(0.242)	(0.220)	(0.190)
NEM Avg.	0.063*	0.027	0.025	0.027	0.025
	(0.031)	(0.021)	(0.019)	(0.018)	(0.015)
Family size	-0.011	0.042	0.044	0.047	0.038
	(0.124)	(0.085)	(0.077)	(0.069)	(0.059)
N	3095	5559	6958	8619	11725

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 13: Outcome Balance Index (2010-2014)

Outcomes	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20
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)
Student rating of teachers	-0.035	0.029	0.007	-0.020	-0.010
	(0.070)	(0.046)	(0.039)	(0.035)	(0.030)
Stud. rating of teach. (w. rem.)	-0.050	0.025	0.009	-0.006	-0.002
	(0.044)	(0.030)	(0.028)	(0.025)	(0.022)
Credit appr. 1st sem.	0.044	0.048	0.036	0.038	0.037
	(0.062)	(0.046)	(0.043)	(0.041)	(0.036)
% Cred. Appr. 1st Sem.	0.002	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes
F. Effect Year	Yes	Yes	Yes	Yes	Yes
F. Effect Degree	Yes	Yes	Yes	Yes	Yes
F. Effect Campus	Yes	Yes	Yes	Yes	Yes
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 bandwidth.
Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 14: Balance Characteristics - Sample 1 (2010-2014)

Sub Sample	(1) Men	(2) Women	(3) Day S.	(4) Night S.	(5) Tec. Dg.	(6) Prof. Dg.	(7) With MH.	(8) Whitout MH.
Deser. 1st sem.	-0.002	0.001	0.000	-0.001	-0.002	-0.005	-0.001	-0.004†
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Deser. 1st year	-0.001	0.000	0.000	-0.004†	-0.002	0.000	0.000	-0.002
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Student rating of teachers	-0.008	0.029	0.022	-0.118†	-0.078	0.146	0.129†	0.049
	(0.049)	(0.130)	(0.049)	(0.064)	(0.064)	(0.111)	(0.071)	(0.061)
Stud. rating of teach. (w. rem	-0.001	0.067	-0.011	-0.070	-0.060	0.010	0.083†	0.050
	(0.033)	(0.103)	(0.034)	(0.066)	(0.049)	(0.094)	(0.049)	(0.041)
Credit appr. 1st sem.	0.034	-0.019	0.032	0.113	0.055	0.122	0.055	0.172*
	(0.041)	(0.119)	(0.061)	(0.072)	(0.050)	(0.125)	(0.067)	(0.071)
% Cred. Appr. 1st Sem.	0.001	-0.002	0.000	0.003†	0.002	0.003	0.000	0.004*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)
N	5368	1657	4809	3268	5403	1958	4379	3068
Opt. Bw.	11.6	10.8	13.8	11.1	12.5	8.8	10.9	13.0

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 15: Balance Characteristics - Sample 2 (2010-2014)

Sub Sample	(1) Men	(2) Women	(3) Day S.	(4) Night S.	(5) Tec. Dg.	(6) Prof. Dg.	(7) With MH.	(8) Whitout MH.
Next Math Course	0.102	0.092	0.049	0.103	0.096	0.266*	0.058	0.134
	(0.067)	(0.112)	(0.067)	(0.084)	(0.069)	(0.105)	(0.070)	(0.088)
Completed Coursework	-0.015	-0.053	-0.020	0.002	0.056*	-0.120**	-0.006	-0.024
	(0.027)	(0.042)	(0.026)	(0.035)	(0.027)	(0.044)	(0.028)	(0.034)
Deser. 1st year	0.013	-0.060**	-0.010	0.007	-0.004	-0.003	0.003	-0.022
	(0.011)	(0.020)	(0.009)	(0.016)	(0.011)	(0.017)	(0.011)	(0.015)
Credit appr. 1st sem.	-0.444	-0.916†	-0.906*	0.178	0.014	-0.715	-0.967*	0.451
	(0.381)	(0.534)	(0.388)	(0.439)	(0.376)	(0.615)	(0.396)	(0.470)
Credit appr. 1st year	-0.654	0.086	-1.141	0.473	0.626	-0.354	-1.408†	1.680†
	(0.802)	(1.261)	(0.799)	(0.952)	(0.814)	(1.221)	(0.838)	(1.000)
% Cred. Appr. 1st Sem.	0.000	-0.002	-0.007	0.006	0.001	0.005	-0.005	0.006
	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.007)	(0.005)	(0.006)
% Cred. Appr. 1st Year	-0.006	0.004	-0.005	-0.003	0.004	0.001	-0.011	0.010
	(0.007)	(0.010)	(0.007)	(0.008)	(0.007)	(0.010)	(0.007)	(0.009)
% Cred. Appr. 1st Sem. from Total	-0.002	-0.003	-0.003†	0.001	-0.001	-0.002	-0.004*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% Cred. Appr. 1st Year from Total	-0.002	0.001	-0.003	0.003	0.002	-0.001	-0.005	0.008*
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
N	4434	1426	4377	2649	4487	1645	3892	2606
Opt. Bw.	11.7	10.8	14.2	11.1	12.7	8.9	11.4	13.0

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 16: Final Results Table - Sample 1 (2010-2014)

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
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)
Student rating of teachers	-0.882	-0.701	-0.548	0.023	-0.069	-0.858	-0.741	-0.564	0.040	-0.067
	(1.124)	(0.774)	(0.671)	(0.608)	(0.516)	(1.122)	(0.774)	(0.671)	(0.608)	(0.516)
Stud. rating of teach. (w. rem.)	-0.139	-0.185	-0.066	0.496	0.587	-0.118	-0.212	-0.075	0.504	0.584
	(1.106)	(0.775)	(0.671)	(0.609)	(0.517)	(1.102)	(0.773)	(0.669)	(0.609)	(0.516)
Credit Appr. 1st sem.	0.020	-0.455	-0.687†	-0.551	-0.596†	-0.023	-0.501	-0.720†	-0.583	-0.625*
	(0.650)	(0.443)	(0.401)	(0.366)	(0.316)	(0.652)	(0.443)	(0.400)	(0.365)	(0.315)
% Cred. Appr. 1st Sem.	0.000	-0.004	-0.011	-0.012	-0.011	-0.003	-0.006	-0.012	-0.013†	-0.012†
	(0.012)	(0.008)	(0.008)	(0.007)	(0.006)	(0.012)	(0.008)	(0.008)	(0.007)	(0.006)
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
N	3681	6661	8348	10389	14232	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. Columns $(1)-(5)$ do not control for any covariable. Columns $(6)-(10)$ include all covariables in the estimation.

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

Table 17: Final Results Table - Sample 2 (2010-2014)

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
Next Math Course	0.215*	0.118†	0.123*	0.090†	0.119**	0.125	0.091	0.101†	0.069	0.098*
	(0.091)	(0.062)	(0.056)	(0.050)	(0.043)	(0.086)	(0.059)	(0.053)	(0.048)	(0.041)
Completed Coursework	0.007	-0.024	0.008	0.002	0.006	-0.003	-0.029	0.003	-0.002	0.002
	(0.034)	(0.024)	(0.021)	(0.019)	(0.016)	(0.034)	(0.023)	(0.021)	(0.019)	(0.016)
Deser. 1st year	-0.001	0.001	-0.007	-0.007	-0.009	0.000	0.001	-0.007	-0.007	-0.009
	(0.013)	(0.009)	(0.008)	(0.007)	(0.006)	(0.013)	(0.009)	(0.008)	(0.007)	(0.006)
Credit Appr. 1st sem.	0.050	-0.448	-0.388	-0.172	-0.323	0.021	-0.449	-0.386	-0.178	-0.331
	(0.492)	(0.337)	(0.298)	(0.270)	(0.232)	(0.495)	(0.337)	(0.298)	(0.270)	(0.231)
Credit Appr. 1st year	1.278	-0.263	-0.091	0.185	0.188	0.901	-0.336	-0.148	0.105	0.100
	(1.033)	(0.713)	(0.638)	(0.574)	(0.495)	(1.029)	(0.708)	(0.632)	(0.569)	(0.490)
% Cred. Appr. 1st Sem.	0.008	0.000	0.000	0.000	-0.001	0.004	-0.001	0.000	-0.001	-0.001
	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)
% Cred. Appr. 1st Year	0.009	-0.004	0.000	0.000	0.003	0.003	-0.005	-0.001	-0.001	0.002
	(0.009)	(0.006)	(0.005)	(0.005)	(0.004)	(0.009)	(0.006)	(0.005)	(0.005)	(0.004)
% Cred. Appr. 1st Sem. from Total	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
% Cred. Appr. 1st Year from Total	0.004	-0.001	0.000	0.001	0.001	0.003	-0.001	0.000	0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
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
N	3095	5559	6958	8619	11725	3095	5559	6958	8619	11725

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.

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

Table 18: Results Table Sample 1 (2010-2014)

Sub Sample	(1) Men	(2) Women	(3) Day S.	(4) Night S.	(5) Tec. Dg.	(6) Prof. Dg.	(7) With MH.	(8) Whitout MH.
Deser. 1st sem.	-0.021	-0.023	-0.005	-0.033	-0.002	-0.052*	-0.008	-0.044*
	(0.014)	(0.024)	(0.012)	(0.020)	(0.014)	(0.023)	(0.015)	(0.018)
Deser. 1st year	0.015	-0.021	-0.007	0.022	0.008	-0.003	0.013	-0.021
	(0.012)	(0.024)	(0.012)	(0.017)	(0.013)	(0.020)	(0.013)	(0.017)
Student rating of teachers	-0.985	0.786	0.622	-0.837	-0.929	0.403	-0.763	-0.256
	(0.840)	(1.413)	(0.823)	(1.046)	(0.837)	(1.383)	(0.976)	(1.052)
Stud. rating of teach. (w. rem	0.401	-1.232	0.509	0.505	-1.066	2.228†	-0.304	-0.147
	(0.809)	(1.539)	(0.831)	(1.027)	(0.858)	(1.277)	(0.973)	(1.048)
Credit appr. 1st sem.	-0.478	-1.053	-1.463**	0.000	-0.694	0.324	-0.874	0.346
	(0.508)	(0.782)	(0.492)	(0.672)	(0.512)	(0.817)	(0.557)	(0.644)
% Cred. Appr. 1st Sem.	-0.006	-0.011	-0.026**	0.002	-0.016	0.016	-0.013	0.009
	(0.010)	(0.014)	(0.009)	(0.014)	(0.010)	(0.016)	(0.010)	(0.013)
N	5368	1657	4809	3268	5403	1958	4379	3068
Opt. Bw.	11.6	10.8	13.8	11.1	12.5	8.8	10.9	13.0

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. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

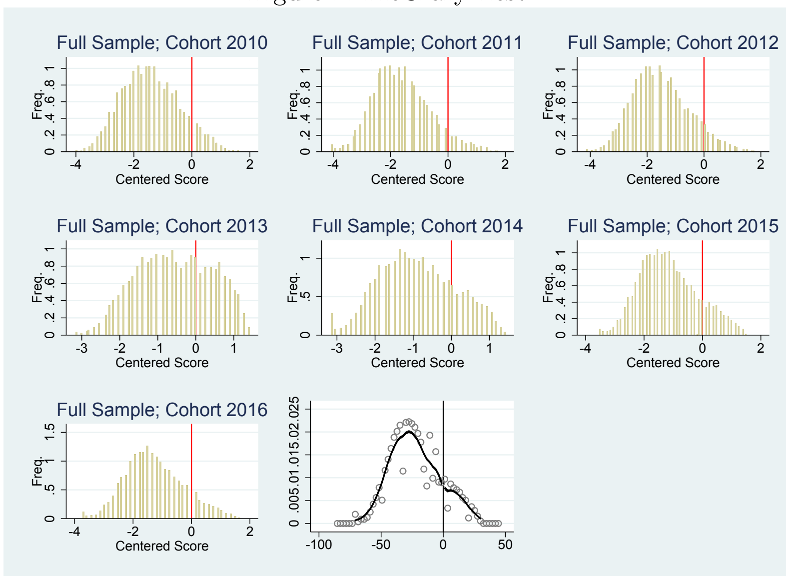
Table 19: Results Table Sample 2 (2010-2014)

Sub Sample	(1) Men	(2) Women	(3) Day S.	(4) Night S.	(5) Tec. Dg.	(6) Prof. Dg.	(7) With MH.	(8) Whitout MH.
Next Math Course	0.102	0.092	0.049	0.103	0.096	0.266*	0.058	0.134
	(0.067)	(0.112)	(0.067)	(0.084)	(0.069)	(0.105)	(0.070)	(0.088)
Completed Coursework	-0.015	-0.053	-0.020	0.002	0.056*	-0.120**	-0.006	-0.024
	(0.027)	(0.042)	(0.026)	(0.035)	(0.027)	(0.044)	(0.028)	(0.034)
Deser. 1st year	0.013	-0.060**	-0.010	0.007	-0.004	-0.003	0.003	-0.022
	(0.011)	(0.020)	(0.009)	(0.016)	(0.011)	(0.017)	(0.011)	(0.015)
Credit Appr. 1st sem.	-0.444	-0.916†	-0.906*	0.178	0.014	-0.715	-0.967*	0.451
	(0.381)	(0.534)	(0.388)	(0.439)	(0.376)	(0.615)	(0.396)	(0.470)
Credit Appr. 1st year	-0.654	0.086	-1.141	0.473	0.626	-0.354	-1.408†	1.680†
	(0.802)	(1.261)	(0.799)	(0.952)	(0.814)	(1.221)	(0.838)	(1.000)
% Cred. Appr. 1st Sem.	0.000	-0.002	-0.007	0.006	0.001	0.005	-0.005	0.006
	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.007)	(0.005)	(0.006)
% Cred. Appr. 1st Year	-0.006	0.004	-0.005	-0.003	0.004	0.001	-0.011	0.010
	(0.007)	(0.010)	(0.007)	(0.008)	(0.007)	(0.010)	(0.007)	(0.009)
% Cred. Appr. 1st Sem. from Total	-0.002	-0.003	-0.003†	0.001	-0.001	-0.002	-0.004*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% Cred. Appr. 1st Year from Total	-0.002	0.001	-0.003	0.003	0.002	-0.001	-0.005	0.008*
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
N	4434	1426	4377	2649	4487	1645	3892	2606
Opt. Bw.	11.7	10.8	14.2	11.1	12.7	8.9	11.4	13.0

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. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

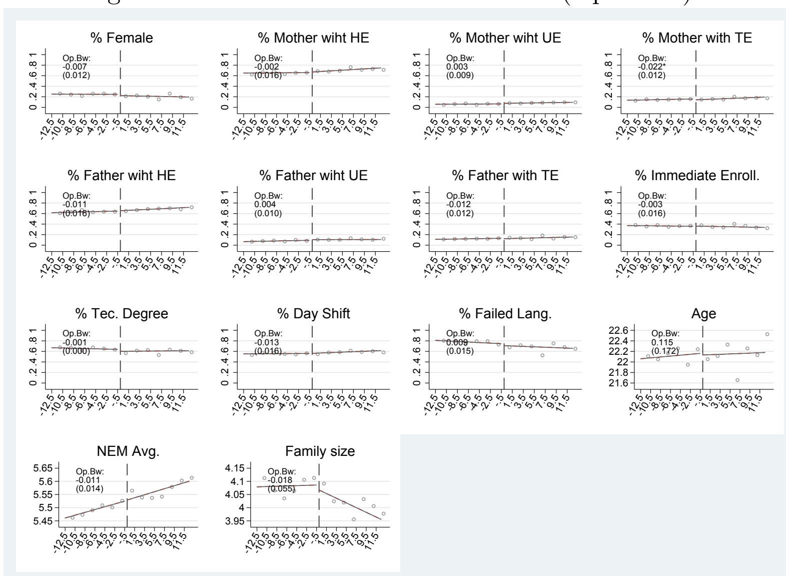
11. Figures

Figure 1: McCrary Test



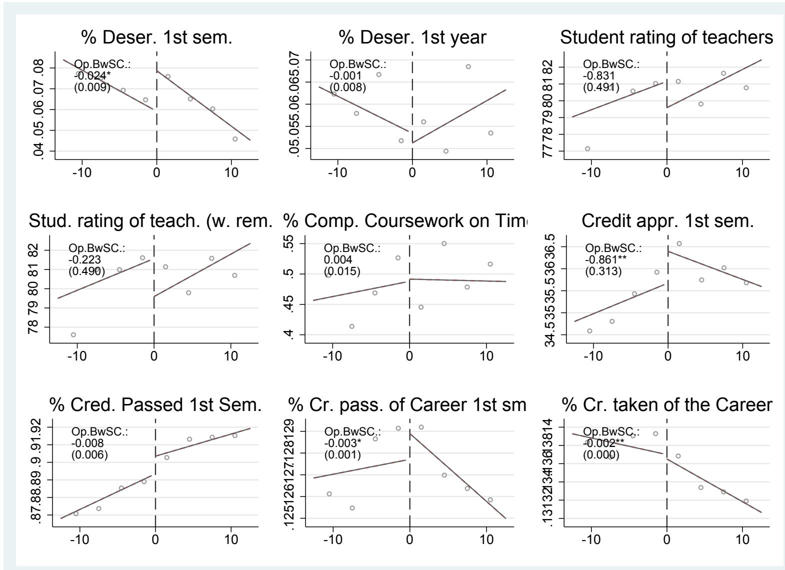
Note. Distribution of Students over diagnostics test score.

Figure 2: Balance Check for Covariables (Opt. BW)



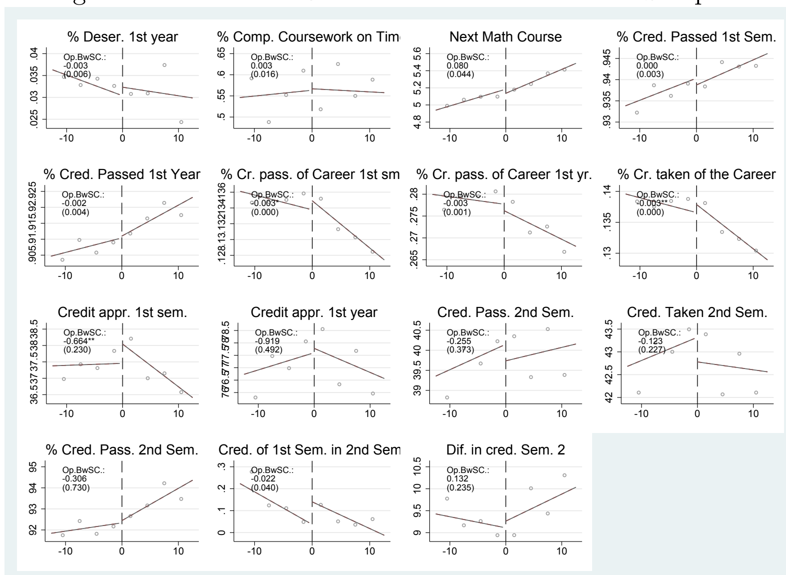
Note. $N = 11006$. Horizontal axis corresponds to the diagnostics test scores centered at the cutoff. Actual values are plotted in bins of size 2. The linear fit represented in solid line uses the CCT optimal bandwidth (12.5). The estimated coefficients of the jump on survey response rate at cutoff score 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: Balance on Outcome Index - Main Analytical Sample



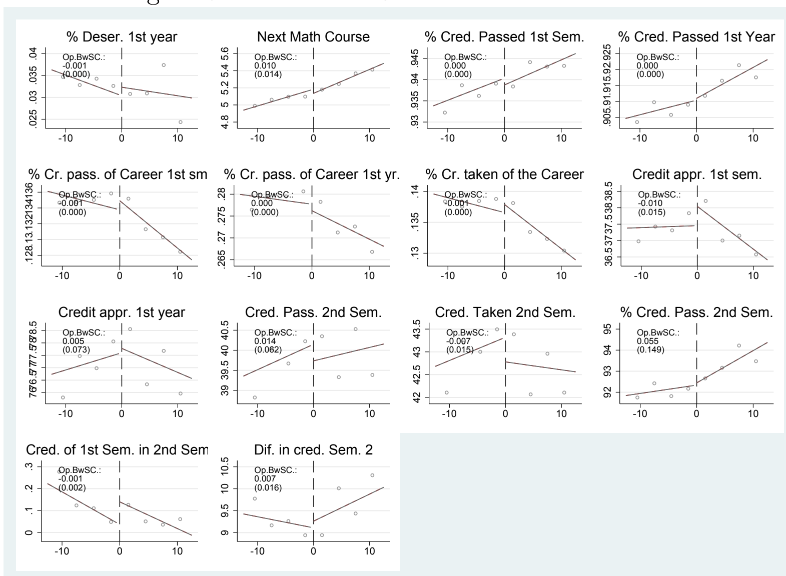
Note. $N = 11006$. Horizontal axis corresponds to the diagnostics test scores centered at the cutoff. Actual values are plotted in bins of size 2. The linear fit represented in solid line uses the CCT optimal bandwidth (12.5). The estimated coefficients of the jump on survey response rate at cutoff score in each model with cohort, general degree and campus fixed effects is presented in the top left area of the graph ("Op. Bw.").

Figure 4: Balance on Outcome Index - Persistance Sample



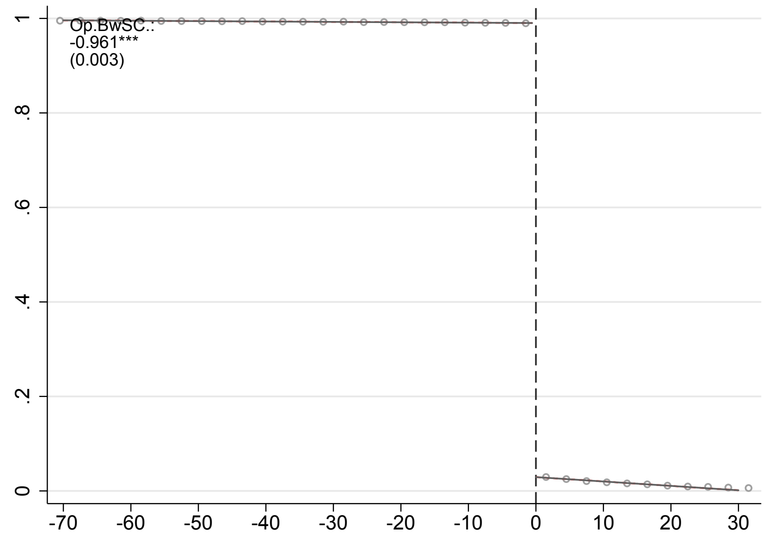
Note. $N = 11006$. Horizontal axis corresponds to the diagnostics test scores centered at the cutoff. Actual values are plotted in bins of size 2. The linear fit represented in solid line uses the CCT optimal bandwidth (12.5). The estimated coefficients of the jump on survey response rate at cutoff score in each model with cohort, general degree and campus fixed effects is presented in the top left area of the graph ("Op. Bw.").

Figure 5: Balance on Outcome Balance Index



Note. 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 2. The linear fit represented in solid line uses the CCT optimal bandwidth (12.5). Coefficients reported in the image are the result of a local regression of the corresponding Outcome Index on the centered selection score, and 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 6: 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. $*p < 0.1$, $**p < 0.05$, $***p < 0.001$.

Appendix A. Tables

Table A.20: Outcome Balance Index - Main Analytical Sample

Outcomes	(1) BW=5	(2) BW=10	(3) BW=12.5	(4) BW=15	(5) BW=20
Deser. 1st sem.	-0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Deser. 1st year	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit appr. 1st sem.	-0.001	-0.029	-0.013	-0.003	-0.017
	(0.049)	(0.033)	(0.030)	(0.027)	(0.025)
% Cred. Appr. 1st Sem.	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
% Cred. Appr. 1st Sem. from Total	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
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
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 bandwidth.
Standard error in parenthesis. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A.21: Outcome Balance Index - Persistance Sample

	(1)	(2)	(3)	(4)	(5)
Outcomes	BW=5	BW=10	BW=12.5	BW=15	BW=20
Next Math C. Grade	-0.034	-0.005	-0.011	-0.010	-0.019
	(0.024)	(0.016)	(0.014)	(0.013)	(0.011)
Deser. 1st year	0.000	-0.001	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Cred. Appr. 1st Sem.	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Cred. Appr. 1st Year	-0.002	0.000	-0.001	-0.001	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
% Cred. Appr. 1st Sem. from Total	0.000	-0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Cred. Appr. 1st Year from Total	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Cr. taken of the Career	0.000	-0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit Appr. 1st sem.	0.007	-0.003	0.008	0.002	0.001
	(0.024)	(0.014)	(0.012)	(0.010)	(0.008)
Credit Appr. 1st year	-0.062	0.003	-0.007	-0.016	-0.047
	(0.109)	(0.064)	(0.058)	(0.052)	(0.045)
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
N	4809	8782	11006	13542	18453

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. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table A.22: Balance on Outcome Balance Index per Subsample - Main Analytical Sample

Sub Sample	(1) Men	(2) Women	(3) F. Lang.	(4) P. Lang.	(5) Day S.	(6) Night S.	(7) Tec. Dg.	(8) Prof. Dg.	(9) With MH.	(10) Whitout MH.
Deser. 1st sem.	0.001	-0.002	0.000	-0.002	0.000	0.000	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Deser. 1st year	0.000	0.000	0.000	-0.001	-0.001	0.000	0.000	-0.001	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Credit Appr. 1st sem.	-0.042	0.046	-0.010	0.020	-0.001	0.006	-0.027	-0.077	-0.052	-0.053
	(0.033)	(0.080)	(0.051)	(0.068)	(0.047)	(0.055)	(0.038)	(0.064)	(0.041)	(0.061)
% Cred. Appr. 1st Sem.	-0.002	0.002	-0.001	-0.001	0.000	-0.001	-0.002	-0.001	-0.001	-0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% Cred. Appr.. 1st Sem. from Total	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
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
N	8078	2467	6987	2178	7544	4039	7293	3398	7535	3469
Opt. Bw.	10.5	10.3	9.1	8.5	12.5	9.9	11.8	9.5	11.0	10.8

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.23: Balance on Outcome Balance Index per Subsample - Persistent Sample

Sub Sample	(1) Men	(2) Women	(3) F. Lang.	(4) P. Lang.	(5) Day S.	(6) Night S.	(7) Tec. Dg.	(8) Prof. Dg.	(9) With MH.	(10) Whitout MH.
Deser. 1st year	-0.001	0.000	0.000	-0.001	-0.001	-0.001	0.000	-0.001	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Next Math C. Grade	-0.025	0.040	0.008	-0.001	0.006	-0.027	-0.018	0.011	-0.001	-0.025
	(0.017)	(0.028)	(0.018)	(0.037)	(0.021)	(0.025)	(0.019)	(0.026)	(0.018)	(0.029)
% Cred. Appr. 1st Sem.	-0.001	0.000	0.000	-0.001	0.000	-0.001	-0.001	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Cred. Appr. 1st Year	-0.002	0.002	0.000	-0.001	0.000	-0.002	-0.001	0.001	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
% Tot. Cred. Appr. 1st Sem.	-0.001	-0.001	0.000	0.000	-0.001	-0.001	0.000	-0.001	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Tot. Cred. Appr. 1st Year	-0.001	-0.001	0.000	0.000	0.000	-0.001	-0.001	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Credit Appr. 1st sem.	-0.004	-0.072	0.012	0.032	0.000	-0.001	0.013	-0.007	-0.026	-0.001
	(0.014)	(0.053)	(0.025)	(0.037)	(0.024)	(0.021)	(0.012)	(0.040)	(0.019)	(0.021)
Credit Appr. 1st year	-0.055	-0.062	0.054	0.061	0.021	-0.075	-0.022	0.084	-0.020	-0.088
	(0.078)	(0.128)	(0.100)	(0.109)	(0.099)	(0.108)	(0.071)	(0.136)	(0.077)	(0.117)
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
N	6732	2132	5816	1907	6166	3246	6714	2853	6245	2924
Opt. Bw.	10.6	10.3	9.2	8.9	12.2	9.6	12.1	9.2	11.1	10.8

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. $\dagger p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.