Information on ability and provision of incentives: regression discontinuity estimates on the effects of assigning college students to remedial courses

Working paper

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Abstract

How do students react to effort-enhancing incentives and information on their academic ability? I present Sharp Regression Discontinuity estimates on the impact that assigning college students' to remedial education has on their subsequent achievements, exploiting a new data set on European Bachelor students. Results indicate that students do not get discouraged when placed in remedial courses. However, the assignment to remediation does not trigger any positive and significant effect on persistence in college, credits accumulation, and the probability to pass the college-level exam of the remedial subject. I also exclude the presence of heterogeneous effects. These findings crucially contribute to the growing literature on measures to enhance college completion and performance.

JEL codes: I21, I23, J24.
Keywords: remedial education; college enrollment, drop-out, and performance; sharp regression discontinuity.

1 Introduction

According to the latest estimates of the returns to higher education, an individual with a tertiary degree is expected to earn on average, each year, 10 to 25% more than a person with only a secondary degree (Oreopoulos and Petronijevic (2013)). Importantly, recent studies suggest that the returns for students on the margin of college attendance could be at least as high as the average returns to college (Zimmerman (2014)). College attendance might also generate non-pecuniary benefits. Kaufmann, Messner, and Solis (2013) show, for instance, that the marriage market returns from being admitted to an elite university are consistent, especially for women. Crucially, as pointed out by Oreopoulos and Petronijevic (2013) the earnings of workers who just complete some college are only marginally higher than those of high school graduates, suggesting that only college completion can trigger a substantial earning premium. Despite this increasing evidence on the overall gains of acquiring higher education, 32% of tertiary students enter university without graduating, across the 18 OECD countries for which there are available data (OECD (2013)). Therefore, it is of primary importance to understand the causes of this phenomenon and to identify the efficient measures to tackle it.

Both economists and policy makers have proposed several policies to enhance college completion, ranging from financial aid to mentoring services. In this paper I focus on remedial courses. These classes are offered to new college students who have weak academic skills. In the United States, public colleges alone spend between $1 and $4 billion in remedial education. The rationale behind this initiative is that students might drop out from university because they lack an adequate preparation to succeed in their tertiary studies. However, its effects might be ambiguous. Remediation should help students recovering or developing these basic skills in order to increase their college retention and improve their performance. Nonetheless, the assignment to remedial courses might well trigger a discouragement or stigma effect, which in turn could affect students' self-esteem and induce them to drop out. If a student is assigned to remediation, he might perceive this as a negative signal on his ability to pursue a college degree. He could also think that his peers will label him as "less academic able". Moreover, remedial courses usually do not count towards degree completion, but work as a prerequisite for college-course attendance. All these factors may contribute to demoralize a freshman and increase his probability of quitting the university. Remedial education might also have heterogeneous effects: it could help the weakest students, but discourage those who would have not expected to be placed in remediation. Finally, remediation can simply be ineffective in reducing students' drop-out probability. Given the increasing interest that colleges and policy institutions are showing for this measure, it is extremely important to identify in which context and for which type of student remedial college education could be useful.

In this paper, I exploit the assignment rule to remedial courses to provide new estimates of the effect of remedial education on students' decisions and performance, implementing a Regression Discontinuity (RD) strategy. I make use of a novel data set coming from the Department of Economics of an Italian university. My results suggest that assignment to remediation does not discourage students who are barely assigned to it from enrolling into the department. At the same time, it does not improve either their overall performance or the performance in the subject of remediation. Importantly, being placed in remediation has no significant effect on their probability to drop out with respect to those students who just escape remediation.

My study contributes in several respects to the growing literature on measures to enhance college completion. First of all, the new data set I collected allows me to identify the effect of assigning to remediation students with different socio-economic origins and covering the entire ability distribution. On the contrary, until now, the empirical evidence on the effects of remedial education has been mostly confined to the experience of American Community Colleges (Bettinger and Long (2009), Boatman and Long (2010), Calcagno and Long (2008), Boatman and Long (2010), Martorell, McFarlin Jr, and Xue (2014), Scott-Clayton and Rodriguez (2012). This is a very peculiar population, composed mostly by minority students, those that have been rejected by private universities, or those that have interrupted their studies right after high school and have later decided to enter tertiary education. The importance of assessing the effect of remedial measures for this population of students is unquestionable. However, given the phenomenon of college drop-out is not confined to them, it is equally important to evaluate the effect of remediation on the average college student.

Secondly, my study focuses on estimating the effect of assigning students to remedial courses. Most of the papers on this topic provide fuzzy RD estimates of remedial education attendance: in short, they compare students close to the cut-off score in the placement test for being assigned to remediation, and instrument the actual attendance of remedial courses with the fact of being assigned to remediation. As pointed out by Scott-Clayton and Rodriguez (2012) the validity of this estimation strategy relies on the assumption that being assigned to remediation has no direct effect on the analyzed outcomes. However, the assignment to remediation might directly influence students decisions via a discouragement or stigma effect and because it provides a signal on the probability to succeed in the college career. For this reason, I provide sharp RD estimates of the direct effect of being placed in remediation.

Third, this allows me to analyze students' first reaction, that is the decision to enroll when placed in remediation. This important outcome has rarely been considered in the previous literature.

Finally, I exploit my rich data set to detect heterogeneous effects. In particular, I explore the possibility that students coming from a vocational school might react differently than students coming from the general track; that high-performing students in high school might get more discouraged than low-performing ones if put in remediation; that male students, usually more over-confident than females, get more demoralized when placed in remediation. My estimates suggest that this is not the case, and I will discuss why this could happen.

The rest of the paper proceeds as follows. Section 2 provides a literature review on the measures proposed to reduce college drop-out and, in particular, on the estimated effects of remedial education. Section 3 describes the Italian university system, and the remedial policies that I analyze. Moreover, it introduces the data set I use. Section 4 describes the empirical strategy. Section 5 provides evidence of the validity of the RD design in the setting analysed. Section 6 presents the results, and section 7 contains the subgroup analysis. Section 8 offers a discussion of my findings. The last section concludes.

2 Related literature

The first economic studies on the topic of higher education focused mostly on the design of efficient policies to boost college enrollment, especially among minority students and those coming from a poor socio-economic background. In the last decades, despite differences by gender, family income and ethnic origin persist, enrollment rates in college have risen steady across all socio-economic groups. On the contrary, completion rates have stagnated and time to completion has increased (Turner (2004)). As a consequence these phenomena have attracted a growing interested among economists. The first hypothesis that has been considered is the straightforward idea that a high drop-out rate and long time to completion might result from borrowing constraints. However, all the papers that have analyzed this explanation (Deming and Dynarski (2009), Dynarski (2008), Stinebrickner and Stinebrickner (2008), Bettinger (2004)) conclude that providing only financial support to students cannot ensure college completion. In other words, as stated by Scott-Clayton (2011), "money may well be necessary but insufficient to improve college outcomes". A series of related papers focus on the impact of alternative and cheaper measures, ranging from mentoring services to peer study groups (Angrist, Lang, and Oreopoulos (2009), Bettinger and Baker (2011), Garibaldi, Giavazzi, Ichino, and Rettore (2012)), others explore the effect of combining financial aid with these different forms of support, or simply to link financial aid to students' performance (Angrist, Lang, and Oreopoulos (2009), Scott-Clayton (2011)). As explain by Angrist, Lang, and Oreopoulos (2009) "The results suggest that the study skills acquired in response to a combination of services and incentives can have a lasting effect, and that the combination of services and incentives is more promising than either alone".

A parallel strand of literature looks at a different explanation, namely that students, when entering college, may lack the adequate preparation to succeed in their university studies. This might lead them to quickly get discouraged, as soon as they encounter some difficulties, and eventually to drop out of college. Alternatively, they could simply need more time to complete their studies, since they have to recover some skills that they should have acquired before entering college. This explains why many colleges in the United States, especially

Community Colleges, provide "weak" students with remedial college courses during the first year. Students who perform poorly in their high school final exam or in standardized exams such as the SAT or the ACT are often required to take a placement test by the college in which they enroll; based on the result of this test they might be placed in remedial courses that should help them regain the basic preparation they need to carry on their studies. Two papers have exploited this assignment rule to estimate, with a Fuzzy RD strategy, the effect of attending remedial education on the probability of drop-out and college performance (Boatman and Long (2010); Calcagno and Long (2008). None of them finds a significant and positive impact of remediation attendance on these outcomes. Importantly, these papers focus on students attending Community Colleges or Public Universities in the United States. These come mostly from a poor socio-economic background, are on average older than students attending private colleges, and might have started working after high school, before coming back to study. The absence of positive results for this specific population is of extreme interest, but might be inconclusive on the effect of remedial education for the average college student. A recent study by (De Paola and Scoppa (2014) provides very optimistic results in this respect. Using a Fuzzy RD design, they find large and positive effects of remedial education on credit accumulation and drop-out reduction for a population of Italian Bachelor students from a Southern Italian university. Given these contradicting results, it is crucial to get more insight on the effectiveness of remediation.

Notably, only a few papers analyze the possibility that the mere assignment to college remedial courses, and not only their actual attendance, might already convey students some information on their chances to succeed in college, and therefore trigger an immediate reaction (Martorell and McFarlin Jr (2011), Scott-Clayton and Rodriguez (2012), Martorell, McFarlin Jr, and Xue (2014)). In particular students assigned to remediation might get immediately discouraged and decide to change college major or not enroll in college at all. Considering this margin of decision is especially important if one wants to use, in the context of a Fuzzy RD design, the assignment to remediation as an instrument for remediation attendance. If this instrument had a direct effect on the outcomes considered, the IV estimation strategy would indeed be invalid. The three studies that estimate the direct effect of assigning freshmen to remedial courses find no significant evidence that this has an impact on their decision to enroll in college. However, even these papers focus on American Community Colleges students. It is important to take into account that these students, before enrolling in Community Colleges, have often applied to private colleges and got a rejection from these institutions. This implies that they might be conscious of their weaknesses, and that, as a consequence, they do not get discouraged if placed in remediation. When, on the contrary, the results of the entrance exam constitute the first signal on the chances to succeed in college, the assignment to a remedial course might be more likely to trigger a discouragement effect. In this paper I analyse this possibility.

Overall, the literature on the effective measures to boost college completion is still scarce and inconclusive. My paper aims at shedding more light on the effectiveness of remedial college education.

3 Institutional setting

The Italian university system has been characterized until now by: the predominance of public universities; moderately low and progressive fees; no selection at entrance apart from specific disciplines such as Medicine or Architecture; a high degree of managerial autonomy for each college, combined with the fact that public funds are allocated mainly on the basis of the number of enrolled students and the number of graduates; very low mobility of students. In this context, in 2004, the Italian Minister of Education introduced the requirement for all public universities to evaluate students' initial preparation and knowledge in the core subject of the chosen field of studies (Ministerial Decree n.270/2004). The rationale behind this initiative was the belief that lack of preparation could be the main cause of an yearly average 30% drop-out rate. Universities were let free to decide how to tackle the possible educational gaps resulting from this evaluation. In response to this vague recommendation, each college, and within colleges, each department, built its own strategy. The majority of the departments introduced, over the last decade, a non-selective entrance test aimed at assessing the basic skills of their freshmen in the core subjects of the department. Others took the chance to introduce also a limited-enrollment rule, so that the entrance test acquired the double goal of selecting the best students, and assessing their basic knowledge. Concerning those students that perform poorly in the placement test, some departments limited themselves to organize compulsory remedial courses with no additional check, incentive or penalization scheme for the students who did not show to recover their gaps. Others created strong incentives schemes, ranging from the prohibition to sustain the regular exam in which the student presented some weaknesses - until he had passed a remedial exam - to the re-enrollment in the first year in case the student had not passed remedial exams. The resulting picture of rules and practices across departments is quite complex, but at the same time constitutes a unique opportunity for evaluating students' reactions to different combinations of signals on their chances to succeed in college and performance-enhancing incentive mechanisms.

In what follows, I am going to present Regression Discontinuity estimates on the effect of being placed in remediation on a variety of students' decisions and outcomes, starting from their enrollment decision (conditional on admission to the Department). I will use a rich data set coming from the Economics department of an university located in the north of Italy. In the academic year 2009/2010, this department introduced a selective and specific entrance exam. To do so, it made use of a standardized exam created by an external institution only for Economics, and currently used by other 14 Econ departments. The exam consists of three sections, testing respectively maths skills, verbal comprehension skills, and logic skills. The admission to the department is based on the weighted average of the scores in the three sections, plus the grade in the high school final exam. Moreover, if a student scores below a certain threshold in the maths section, he receives "additional educational duties" (henceforth OFA, the Italian acronym). In this department the consequences of receiving these remedial duties are tough: first of all, students have to take a remedial maths exam; secondly, they cannot take the regular maths exam until they have passed the remedial one; they are offered a remedial course of 21 hours in the month of October after enrollment, and a minimum of five retakes for the remedial exam, over the course of the first year; however, if they are not able to pass none of these retakes during the first year, they are automatically re-enrolled in the first year, the following September.

In the database I personally collected, I observe all the 2928 students who have participated to the entrance exam over the four years since it has been introduced. I have information on their age, sex, nationality, city of residence, type of high school attended, and location of the high school. Moreover, I have the results of the entrance exam, separately for each section, and I can track the decision to enroll, for those students who are admitted, the decision to drop out during the course of studies, the grade in the regular maths exam, the number of credits accumulated, students' GPAs, and eventually their time to complete a degree. The aim of my work is to provide estimates on the effect of assigning students to remedial education, for each of these outcomes. However, I want to stress again, that the effect that I identify on a certain outcome is always conditional on the impact that this policy has on the previous decisions. In tables 1, 2 and 3 I report the descriptive statistics for the sample under study. Three features of the data are worth mentioning: 95% of students are admitted among those who participate to the exam, which implies that at the margin of selection there is no much action in this Department, (table 1). Secondly, a large majority of students, approximately 75%, receives OFA in my sample, (table 1). This figure is very similar to the percentage reported in Scott-Clayton and Rodriguez (2012). It will be important to take this into account, in order to understand the results that will follow. Third, it is clear that students who receive OFA are different with respect to those who escape remediation, in terms of baseline characteristics . The percentage of immigrants is higher among the former - although, in absolute terms, is quite low; the same is true for the percentage of students performing poorly in high school, or for the percentage of students coming from a vocational school, (table 2).

Considering the first outcome of my analysis, the decision to enroll - table 3 - it is interesting to notice that students in the need of remediation are more likely to enroll with respect to those with no OFA. In the next paragraph I will devote a few words to explain why this could be the case. Regarding the drop-out decision, the figures seem to confirm the expectations: students with OFA, or the weakest students, seem more likely to give up after one year [1]. Credits accumulated and the probability to pass college-level maths are also lower for students placed in remediation with respect to those who escape it. In the next paragraph I will explain how I control for these differences in order to isolate the effect of placing students in remedial education on these outcomes.

However, before entering into the empirical strategy in details, it is important to understand how Italy compares to other OECD countries, in terms of the main outcome of interest, and to what extent the sample under study could be representative of the entire population of Italian undergraduate students. Figure 1 shows the 2011 average college completion rates respectively across 18 OECD countries, all Italian undergraduate programs, and for the students who enrolled in the Economics department under study. Italy completion rates are in line with the OECD average. Students enrolled in the Economics department I consider do slightly better than this. However, the characteristics of the sample of students I observe reflect quite well those of the overall population of Italian undergraduate students, as shown in table 4. This is true in particularly for what concerns the ability composition of students [2]. In light of these figures, the fact that the sample under study comes from a single department of a specific major should not represent an important limitation of this paper.

4 Empirical Strategy

The goal of this paper is to provide causal estimates of the impact of assigning students to remedial education on their college performance. The simple comparison between the sample means in the outcomes of interest of the group who was placed in remediation and the one that escaped it cannot help us to identify this effect, as the two groups are quite different in terms of baseline characteristics. Even when explicitly controlling for these covariates, simple

[1] Importantly, I analyze all the outcomes for the entire sample of students that participated to the entrance exam. This means, for instance, that drop-out is equal to 1 both for a student who attend the first year and the abandon the department, and for one who decided not to enroll at the very beginning of the year; and I also assign to this student 0 credits, when looking at credits accumulation.

[2] Ability here is measured in terms of the performance at the high school final exam. The grade in this exam goes from between 60 and 100. I then define as low-ability students those who score below 70, as medium-ability those who score between 70 and 89, and as high-ability those who get more than this.

OLS estimates would probably tend to downward bias any positive effect that the assignment to remediation might have. This is because students might also differ in terms of unobserved characteristics, such as self-esteem or aspirations, which in turns can have an influence on the outcomes considered.

However, following Martorell and McFarlin Jr (2011), Scott-Clayton and Rodriguez (2012), and Martorell, McFarlin Jr, and Xue (2014) the rule to assign students to remediation can be exploited to identify the effect of interest using a regression discontinuity (RD) design. The intuition is the following. The assignment to remediation is completely determined by the score in the maths section of the entrance exam. Clearly, we can expect that the performance in this test and students' subsequent achievements in college would be somehow related. However, it seems reasonable to assume that this relationship would be smooth. This should also be the case around the score that determines the assignment to remediation. Nonetheless, the fact that only those students who score below this threshold are assigned to remediation and those who score above it are not, generates a shard discontinuity in the treatment as a function of the test score. Therefore, under the assumption that nothing else changes at that threshold, any discontinuity in the relationship between the outcomes and the maths score, around the cutoff value, could be interpreted as evidence of a causal effect of assigning students to remediation.

Imbens and Lemieux (2008) formalize this idea using Rubin's potential outcomes framework. In general, when considering the impact of a policy intervention, we can imagine that, for each individual i, there exists a pair of "potential" outcomes: $Y_i(1)$ if he were exposed to the treatment, and $Y_i(0)$ if not. The causal effect of receiving the treatment for this individual would be $Y_i(1) - Y_i(0)$. Unfortunately, this difference can never be observed. In the same way, in the RD setting, we can think that there are two underlying relationships between the average outcome of interest and the assignment variable X - here, the performance in the maths test - represented by $E[Y_i(1)|X]$ and $E[Y_i(0)|X]$. Crucially, in the typical RD setting, all the individuals on a side of a certain cutoff value c of the assignment variable are exposed to the treatment, and all those to the other side are denied it - in the contest of interest, all students who score below a certain threshold in the maths section of the entrance exam are assigned to remediation, and all those who score above it, can escape it. Therefore, we can only observe $E[Y_i(1)|X]$ to the left of the cutoff and $E[Y_i(0)|X]$ to its right. However, this allows to estimate the following expression

$$lim_{\epsilon \to c^+} E\left[Y_i|X_i = c + \epsilon\right] - lim_{\epsilon \to c-} E\left[Y_i|X_i = c - \epsilon\right]$$

which will identifies the average treatment effect at the cutoff c, $E[Y_i(1) - Y_i(0)|X == c]$, under the assumption that the underlying functions $E[Y_i(1)|X]$ and $E[Y_i(0)|X]$ are continuous in X, especially around the cutoff c. Basically, this continuity condition allows to use the average outcome of those right above the cutoff (who escape the treatment) as a valid counterfactual for those right below it (who received the treatment). For this condition to be plausible, we must be willing to assume that "all other factors" determining Y evolve "smoothly" with respect to X. Importantly, this will be the case only if individuals have imprecise control over the assignment variable. Then, even though some would be especially likely to have values of X near the cutoff, everyone will have approximately the same probability of having an X that is just above or just below the cutoff. In other words, in a neighborhood around the threshold, the variation in the treatment will be as good as randomized. And as in a randomized experiment, this implies that the distribution of both the unobservable and observable factors that influence the outcomes of interest should not change discontinuously at the threshold.

In the setting here analysed, assuming that individuals have imprecise control over the assignment variable means that students should not be able to exactly determine their performance in the exam, and that this should be, at least in part, driven by chance. At the same time, it is important that also in the correction phase, no one could manipulate the grades (Jacob and Lefgren (2004)). In this context, the entrance exam is created by an external institution and it is corrected by a computer. Hence, it is hard to think of a way in which students, or professors in the department could have precise control over the maths score. However, in the next paragraph I am going to provide some more formal evidence for this.

To practically implement the RD design, following Lee and Lemieux (2010), I will estimate a local linear (LL) regression

$$Y_i = \alpha + \beta_1 D_i + \beta_2 NormScore_i + \beta_3 D_i NormScore_i + W_i \pi + CohortFE + \varepsilon \quad (1)$$

restricting the estimation sample to those students who score in a small neighborhood around the threshold, $c - h \leq X_i \leq c + h$. Here Y represents the outcome of interest. In this setting it will be, alternatively, enrollment in college, drop-out in the first or second year, credits accumulated by the end of the first or second year, or performance in college-level maths. D is a binary variable being equal to one below the threshold for remediation assignment and 0 otherwise. $NormScore_i$ represents the distance between the score in the maths section of the entrance exam and the cutoff that determines the assignment to remediation. W_i is a vector of controls including sex, immigration status, performance in the high-school final exam, an indicator variable for the type of high school attended, and high school province fixed effects. Finally I include cohort fixed effects. In this regression, the main coefficient of interest is β_1 which measures the discontinuity in the intercept in the relationship between the outcome of interest and the performance in the maths test. Under the assumption that none of the actors in this setting could have precise control over the assignment variable, this discontinuity will identify the causal impact of assigning students to remediation, for those students who score close to the cutoff. In what follows, I will report the estimates of β_1 for three different values of the bandwidth h, respectively ($h = 2, 1, 2.5$). Following Lee and Lemieux (2010), to assess the robustness of the RD estimates, in all the tables, I will also show the results from a flexible polynomial regression on the entire sample

$$\begin{aligned} Y = \alpha + \beta_1 D_i + \beta_2 NormScore_i + \beta_3 NormScore_i^2 + \\ + \beta_4 D_i NormScore_i + \beta_5 D_i NormScore_i^2 + W_i \pi + CohortFE + \varepsilon \end{aligned} \quad (2)$$

In the next paragraph, before moving to the results, I provide some evidence that the RD design is a valid estimation strategy in this setting.

5 The validity of the RD design

Even if there is no direct way to test that individuals do not have precise control on the assignment variable, there are two procedures to indirectly check for the validity of the RD design. The first one is to inspect whether the distribution of the assignment variable exhibit any discontinuity at the cutoff. As state by Imbens and Lemieux (2008) in principle, the continuity of the density of X at c is not required, but a discontinuity is suggestive of a violation of the no-manipulation assumption. If in fact students manage to manipulate their maths test score in order to be on a specific side of the cutoff, then we should observe an unusual concentration of students scoring right above or below the threshold. Figure 2 shows the distribution of this score. As each year the threshold for placing students in remediation was changed, I have normalized the grade so that the 0 corresponds to the cutoff. Each correct answer in the exam gives 1 point, while wrong answers are penalized by 0.25, and unanswered questions are not punished. The normalized distribution looks left skewed, with a mean of -2.78, indicating that students are performing quite poorly on average. There is, however, a lot of variation in students' performance, with a standard deviation of 3.65. More importantly for the RD design, it does not seem that a disproportionate fraction of students concentrates right below the threshold, which would suggest that many of them are acting in order to be assigned to remediation. At the same time, there is no sign that students are answering just enough questions to escape from remediation, which would result in a jump in the distribution above the cutoff. Therefore, the graphical analysis of the distribution suggests that students, nor professors, have precise control over the assignment variable. A McCrary test (McCrary (2008)) supports this believe, as the null hypothesis of no jumps in the distribution of the maths score, at the cut-off, cannot be rejected (results of the test are available upon request).

A second way to test for the validity of the RD design is to inspect whether students' baseline observable characteristics, that might influence the outcomes of interest, do not exhibit any discontinuity at the cutoff in their relationship with the assignment variable. Baseline covariates such as the high-school final grade, sex or immigration status are, by definition, determined prior to the assignment to remediation. Hence, there should be no reason to expect a jump at the threshold in their relationship with the assignment variable. Again, any evidence of such discontinuities would suggest that students are in some way able to manipulate their performance in the entrance exam. As we can see from the graphical analysis, figure 3, it does not seem possible to detect any visible jump in relationship of the baseline covariates with the assignment variable at c. Table 5, showing all the estimated discontinuities, confirms this intuition, as no discontinuity turns out to be significant.

Therefore, in the context of analysis, the RD design appears a valid estimation strategy to identify the effect of assigning students to college remediation on their performance in college. The next session will therefore discuss the results of this estimation procedure.

6 Results

The data set I collected allows me to study how students react to the assignment to remediation along different margins of decisions. In this section I illustrate and discuss the estimated impact on each of them.

The decision to enroll. One of the main contributions of my study is that I am able to analyse how undergraduate students immediately react to the fact of being put in remediation. In my context, the performance in the entrance exam constitutes the first signal on the ability to perform well in college. Hence, students might react strongly to it, and in particular they can get immediately discouraged and decide not to enroll in the department they had chosen. Figure 4 plots the likelihood to enroll as a function of the score in the math section of the entrance exam. In detail, each dot represents the probability to enroll averaged across all students obtaining a certain maths grade. The x-axis is normalized so that the zero corresponds to the threshold for the assignment to remediation - which varies over years. Students who score at or below 0 are placed in remediation, while those who score above are not. The lines are linear fits of the dots, estimated separately on each side of the threshold. The graph shows two main facts: first of all, there does not seem to be a jump in the probability to enroll at the threshold, which suggests that assignment to remediation does not trigger an immediate discouragement effect. However, an interesting feature of the data is that the probability to enroll appears to decline as the grade in the maths exam increases. My data set allows me to follow those students who participate to the entrance exam at the department of Economics, but then decide to enroll in another department of the same university[3]. The analysis of their choices suggests that this pattern is explained by the fact that students who score higher in this entrance exam are the ones who have more chances to contemporaneously apply and be accepted to other departments. [4] Table 6 shows the point estimates of the effect of being placed in remediation on the probability to enroll in the department. The table confirms what the graphical analysis suggests: in none of the specifications I can reject the null that, on the margin for remediation, assigning a student to a remedial course affects his decision to enroll with respect to a student who scores right above the threshold.

The decision to drop out after the first year. In principle we would like a student to react constructively to the fact of being placed in remediation. He should consider it a signal that he has to work hard during the first year in order to succeed in his college studies, and that the assignment to remediation could be beneficial for him. If this is the case, we should expect him to have a lower probability to quit the university with respect to a student who escapes remediation. However, especially for a student at the margin for needing remediation, assignment to remediation might discourage him over the course of the first year; in the context of study, if a student does not pass the remedial exam in the first year, he cannot enroll in the second year; at the same time, he has at least five retakes possibilities to pass it. Nonetheless, the strong penalization associated to a failure might induce him to focus exclusively on the remedial exam, with the consequence of finding himself lagging behind in the other courses at the end of the first year. This can lead to the undesired result of increasing his probability of a drop-out. The top-left panel of figure 5 plots the likelihood to drop out after one year as a function of the performance in the maths section of the entrance exam. As expected, students who perform worse in the exam have a higher chance to quit the university. However, the

[3]Unfortunately I cannot track the choices of those students who take the entrance exam and then either enroll in a different university or do not enroll at all in college

[4]These results are not shown in the papers but are available upon request.

function does not exhibit any jump at the threshold for remediation assignment. The point estimates in the first row of table 7 suggest the presence of a discouragement effect for students scoring right below the threshold for remediation with respect to those just escaping it, but they are not significant in any of the specifications.

Credits gained by the end of the first year. The results discussed until now seem to exclude the possibility that assignment to remediation discourages students who barely need it. However, opponents of remedial policies argue that they can still be detrimental if they drain students resources away from college-level courses. Students in remediation are supposed to put extra effort in their first year in order to recover their initial weaknesses, and at the same time, try not to lag behind in their regular courses. Nevertheless, we might expect them to gain less credits during the first year, if they decide to focus on the remedial course before studying for college-level ones. Figure 5 displays the credits accumulated in the first year as a function of the maths grade in the entrance exam. The overall pattern indicates that weakest students take less credits over the course of the first year. However, assigning students to remediation does not seem to worsen this trend. The estimated jump in this relationship, second row of table 7, is negative, suggesting that students who are barely assigned to remediation gain 1 to 4 credits less than students who barely escape it. This corresponds to a 10 to 20% decrease in credit accumulation with respect to the sample mean. Nonetheless, the estimated discontinuity is not significant in any of the specifications.

Performance in the subject of the remedial course. The main goal of remediation is to help students recovering some basic notions in the subject of the remedial course, in order for them to be able to pass the college-level exam. Even if a student decides not to attend the remedial course, the mere assignment to it should induce him to work harder in the subject of remediation. Hence, assignment to remediation could have a positive effect on the probability of passing the college-level exam. The bottom-right panel of figure 5 suggests that this is not the case in the studied sample: the relationship between the probability of passing college-level maths and the grade in maths at the entrance exam exhibits no discontinuity at the threshold for remediation assignment. In table 7, the point estimates of the effect of assignment to remedial maths on the probability to pass regular maths for students who are at the margin for remediation are unstable across the different specifications, and not significant in any of them.

Performance in the second year. The beneficial effects of assigning a student to remediation, if any, might appear only in the second year, when he has supposedly recovered from his initial difficulties. This could be even more so in a context in which students placed in remediation do not seem to get discouraged or to lag behind their peers in the first year. If this is the case, we should observe that assignment to remediation has a positive effect on credits accumulated in the second year and a negative effect on second year drop-out. The graphical analysis in figure 5 goes against these conjectures. The graphs of second-year credits and second-year drop-out as a function of the maths score in the entrance exam show no visible discontinuity at the threshold for assignment to remediation. Point estimates in table 7 suggest that assigning students to remediation increases the gap between them and those who escape it over time, but no specification delivers significant results.

7 Subgroup analysis

Finding no significant results for the entire sample can mask heterogeneous and opposite effects for specific subgroups. The assignment to remediation might be beneficial for students coming from a vocational school, or for those with a low performance in high school who can have low expectations about their chances to succeed in college; but it could demoralize high-performing students and students coming from the general track if these have higher priors about their ability to complete university. Finally, several behavioural studies (Buser, Niederle, and Oosterbeek (2012), Niederle and Vesterlund (2010), Niederle and Yestrumskas (2008)) suggest that men tend to be more over-confident than women, hence male students might react worse than female students if placed in remediation. The data set under analysis allows to test these predictions. Figure 6 shows the likelihood to enroll as a function of the maths grade in the entrance exam for the following subgroups: male and female students,

students at different intervals in the distribution of high-school final grades, and students coming either from a vocational high school or from the general track. No visual discontinuity could be detected from the graphical analysis. Table 8 presents the estimated jumps in the enrollment decision, for all the subgroups. None of the estimates comes up significant, with the exception of those for males. However, neither these are robust across different specifications. Moreover, it is important to bear in mind that testing for multiple subgroups corresponds to multiple hypothesis testing, and therefore it increases the probability of committing the TYPE I error. In details, when testing for n different interaction terms, the probability of getting k significant p-values with zero true effects is given by:

$$p\left(k,n\right)=\binom{n}{k}\alpha^{k}\left(1-\alpha\right)^{n-k}$$

In order to take this into account, I also consider more conservative significance levels such as those derived from the Bonferroni correction procedure or the Benjamini-Hochberg one. [5] In this context the two procedures lead to the same conclusion. Using either of the two methods makes me unable to reject the null of no discontinuity in the enrollment decision at the threshold, as well as in the other outcomes, for all the subgroups [6].

8 Discussion

My results add to the prior literature by imposing a word of caution on the effectiveness of remedial education for all undergraduate students - and not only for those atttending Community Colleges. The studies on Community College students conclude that remedial courses do not improve the chances to succeed in college if offered to that specific population.

[5] The Bonferroni correction procedure prescribes that, when testing for n hypothesis, and considering a significance level π, only hypotheses with associated p-values $\leq \frac{\pi}{n}$ should be rejected. The Benjamini-Hochberg method, instead, works as follows: given a set of hypotheses $H_1, H_2, ..., H_m$, let $p_1, p_2, ..., p_m$ be the corresponding p-values, and denote by H_i the null hypothesis corresponding to p_i. Order the p-values $p_1, p_2, ..., p_m$ and let k be the largest i for which $p_i \leq \frac{i}{m}\alpha$; then reject all H_i with $i = 1, 2, ...k$. The two procedures are similar but in general the Benjamini-Hochberg one has the advantage of minimizing the probability of committing the TYPE II error.

[6] The results for the other outcomes are not shown here but are available upon request.

On the contrary, the analysis conducted by De Paola and Scoppa (2014) on Italian Bachelor students suggests that, in this context, college remediation can prove to be effective in reducing students' drop-out and improving their performance. Their study considers students enrolling in various departments, while mine is restricted to a department of Economics. However, the two populations of students appear similar in terms of baseline characteristics. Nonetheless, the remedial programs offered in the university of Calabria and in the one I study differ in many respects: the one considered by De Paola and Scoppa (2014) costs 1,000 euros per student, students are assigned to the remedial course if they perform below a certain threshold both in maths and writing, the optional remedial course lasts 160 hours, and students are not re-examined at the end of it. In the context analsyed here, remediation is estimated to cost around 2,000 euros every year in total, it focuses exclusively on maths skills, and consists of a 21-hours course. Importantly, students have to pass an exam at the end of it, they have several retakes possibilities to do so during the first year, and this is a prerequisite for college-level maths. Moreover, students who fail in the remedial exam during the first year cannot enroll in the second one. Finally the skills tested in the two placement exams and the content of remedial courses might differ. Hence, any comparison between these two studies has to take all these differences into account. However, precisely because of these differences, my study contributes to identify which elements of remedial policies are important to ensure its effectiveness, being these its cost or the incentives and penalization associated to it. My results confirm the reassuring conclusions of Martorell and McFarlin Jr (2011), Scott-Clayton and Rodriguez (2012) and Martorell, McFarlin Jr, and Xue (2014) that students at the margin for remediation do not need to get discouraged if placed in remediation, and this is true for any subgroup considered. This might be due to the fact that the great majority of students is assigned to a remedial course; moreover, the fact that students have several possibilities to retake the remedial exam can help avoiding any initial discouragement. On the other hand, the absence of any positive result on post-entry outcomes, such as drop-out, credit accumulation, and the probability of passing college-level maths for students close to threshold for remediation is more worrying. This is especially so if we consider the structure of incentives and punishments included in the remedial policy. In this respect, the fact that more than 70% are placed in remediation could prevent the assignment to remediation to deliver any informative signal, and therefore to induce students to increase their effort. Unfortunately, these are only speculative explanations, and the context I study does not allow me to identify the relative importance of all these factors in driving the results I find.

9 Conclusion

Policy makers and universities have started to show a growing interest for college remedial education as a measure to reduce the severe problem of college drop-out. Identifying which aspects of remedial policies are more effective and for which types of students they could be more useful is of primary importance. This study makes several contributions in this respect: it makes use of a novel and rich data set of European Bachelor students. This allows to improve our understanding of how college students react to the provision of ability information and performance-enhancing incentives delivered by the assignment to remediation. Moreover, following Scott-Clayton and Rodriguez (2012), I make use of a sharp regression discontinuity design to estimate the effect of the assignment to remediation, and not only remediation attendance, on students' decisions and performance. This allows me to estimate if the assignment to remediation immediately discourages students from enrolling in the chosen department. Furthermore, my data set permits me to track students over their career and to identify if, when and how students react to the fact of being put in remediation. Finally, information on students' baseline characteristics allows me to detect heterogeneous effects. I find no significance evidence that assigning students to remediation affects their decision to enroll. The estimated effects on post-entry outcomes are also insignificant. An accurate subgroup analysis excludes the possibility of heterogeneous effects. It is important to bear in mind that the RD results speak for those students who are at the margin for remediation need and cannot say anything for those who perform poorly in the placement test, presumably the weakest students. However, in light of the recent contributions of the literature on remedial education, my results suggest that further research is needed to understand which aspects of remedial policies are most effective in boosting students' performance and reducing college drop-out. Exploiting the variation in the structure of remedial policies offered by departments that use the same placement test is crucial in this respect.

10 Tables and Figures

Table 1: Students admitted to the department of Economics studied

	Admitted
Total	2,785
Over participants (%)	0.95
In remediation (%)	0.77

Note: In the first row, the table reports the total number of students admitted to the Economics department studied between 2009/10 and 2012/13; in the second row, the proportion of students admitted over those who participated in the entrance exam; and in the third row, the percentage of students that was assigned to remediation, over the admitted students

Table 2: Baseline characteristics of the estimation sample

	Admitted	In Remediation	Not in Remediation
Female	0.48	0.52	0.36
Immigrant	0.08	0.08	0.06
Low high-school grade (60-69)	0.46	0.47	0.40
Medium high-school grade (70-89)	0.33	0.32	0.36
High high-school grade (90-100)	0.18	0.17	0.21
Vocational track	0.41	0.47	0.22
General track	0.36	0.28	0.62
Other high schools	0.23	0.24	0.17

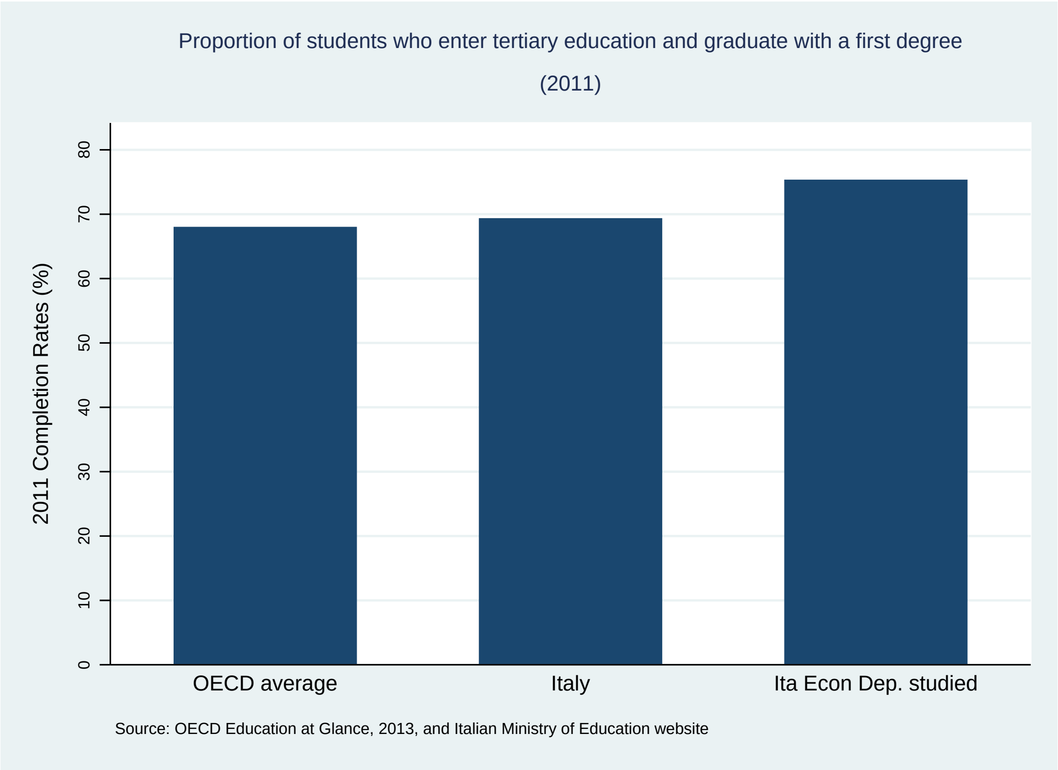
Note: the table reports the percentage of students belonging to a specific subgroup (indicated in the first column) with respect to the entire group of admitted students (column 2), the group of students assigned to remediation (column 3), and the group of students that escaped remediation (column 4).

Table 3: Sample means of the outcomes of interest

	Admitted	In Remediation	Not in Remediation
Enrollment	0.84	0.85	0.79
1st year drop-out	0.27	0.28	0.24
2nd year drop-out	0.34	0.35	0.28
1st year credits	22	21	27
2nd year credits	26	25	33
Passing college-level maths	0.40	0.35	0.55
College-level maths grade	22	22	24

Note: the table reports the mean of the outcomes considered (indicated in the first column) for the entire group of admitted students (column 2), for the group of students assigned to remediation (column 3), and for the group of students that escaped remediation (column 4).

Figure 1: College completion rates



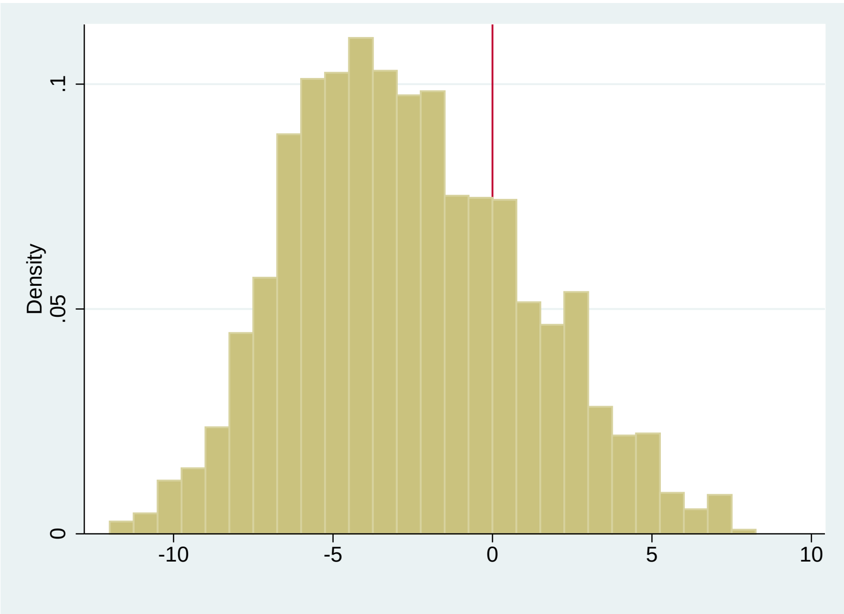
Note: the data for the OECD average completion rates were collected through a special survey undertaken in 2012 by the OECD. For half of the countries, completion rates are constructed using a true cohort method, and represent the proportion of graduates (within N years) among a given entry cohort. The completion rates for the other countries are calculated from cross cohort methods as the ratio of the number of students who graduate with an initial degree during the reference year to the number of new entrants in this degree n years before, n being the number of years of full-time study required to complete the degree. I follow this method to construct the figures for Italy, using the data provided by the Ministry of Education. The 2011 completion rates refer then to ratio of the number of students who got an undergraduate degree in the academic year 2010/2011 to the number of students who enrolled in an undergraduate program in 2008 - as it should take 3 years to complete such a Bachelor degree.

Table 4: Baseline characteristics of students enrolled in Italian undergraduate programs

	All Italian departments	Economics department studied
Female	54.86	46.67
Immigrant	4.73	8.68
Low high-school grade (60-69)	26.13	25.10
Medium high-school grade (70-89)	51.84	53.80
High high-school grade (90-100)	17.85	17.02
General track	56.06	34.46

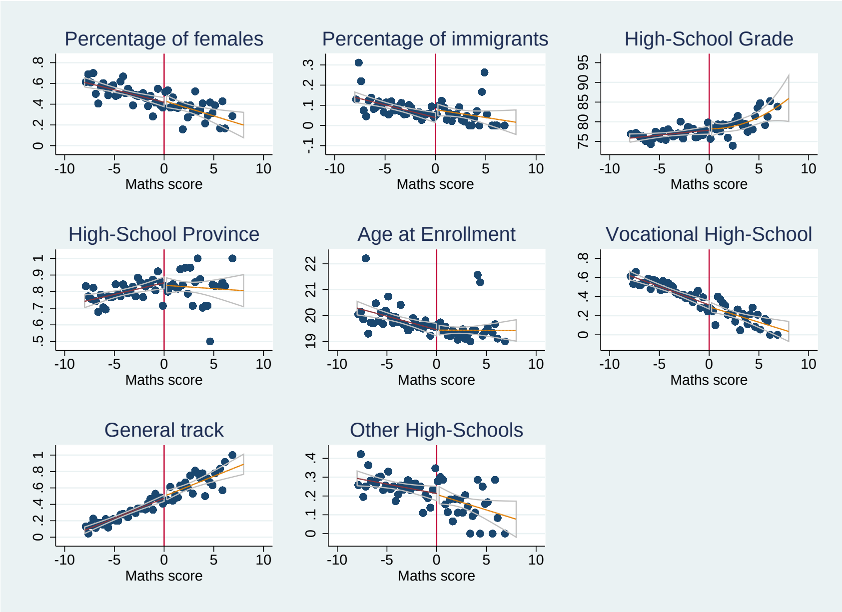
Note: the table reports the percentage of students belonging to a specific subgroup (indicated in the first column) with respect to the population of enrolled students in all Italian undergraduate programs (column 2), or over the enrolled students in the undergraduate program of the Economics deparment studied (column 3)

Figure 2: Distribution of the assignment variable, relative to the cutoff



Note: the figure reports the histogram of the maths score in the entrance exam, which represents the assignment variable in this setting. The distribution is normalized so that 0 corresponds to the cutoff below which students are assigned to remediation.

Figure 3: Baseline characteristics as a function of the assignment variable



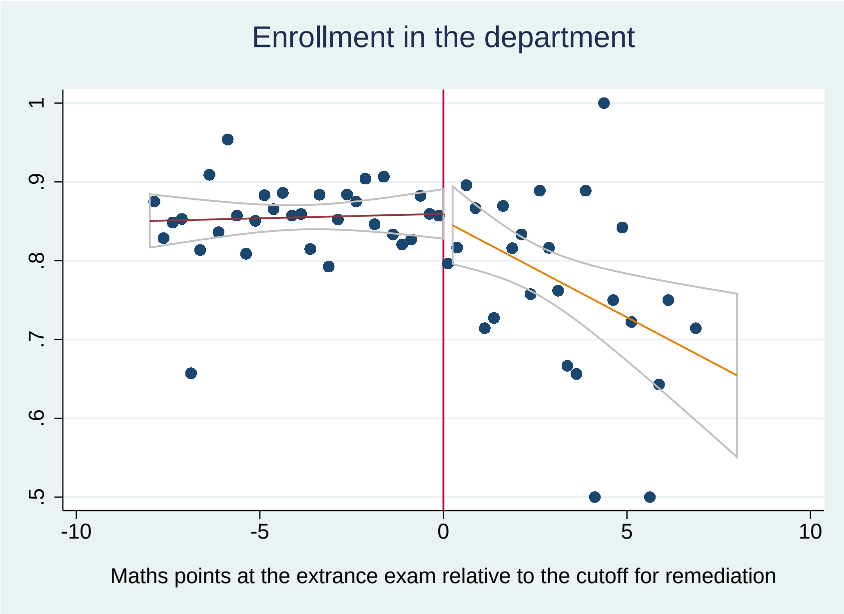
Note: in each graph the dots represent averages of the outcome variables computed for each value of the assignment variable (maths score). The lines correspond to linear fits of the dots, computed separately on each side of the cutoff for remediation assignment.

Table 5: Estimated discontinuities in baseline characteristics

	Local linear (±2)	Local linear (±1)	Local linear (±2.5)	Polynomial
Female	-0.08	-0.09	-0.06	-0.01
	(0.07)	(0.10)	(0.06)	(0.04)
Immigrant	-0.05	-0.07	-0.04	-0.02
	(0.04)	(0.05)	(0.03)	(0.02)
High-school grade	-1.69	-1.49	-1.79	0.25
	(1.64)	(2.39)	(1.46)	(0.94)
Age at enrollment	-0.14	-0.21	-0.11	0.03
	(0.25)	(0.41)	(0.22)	(0.13)
Vocational high-school	0.02	0.13	-0.01	0.00
	(0.06)	(0.09)	(0.05)	(0.04)
General track	0.02	-0.07	0.04	-0.02
	(0.07)	(0.10)	(0.06)	(0.04)
Other high-schools	-0.04	-0.07	-0.03	0.02
	(0.06)	(0.09)	(0.05)	(0.03)
N	844	458	1,042	2,662

Note: the first column indicates the dependent variable. Estimation methods: Local Linear Regression (LL) with bandwidth h = 2, 1, 2.5, respectively in columns 2, 3, and 4; Polynomial regression with 2nd-order polynomial in column 5. Robust standards errors in parenthesis. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by **.

Figure 4: Enrollment decision as a function of the assignment variable



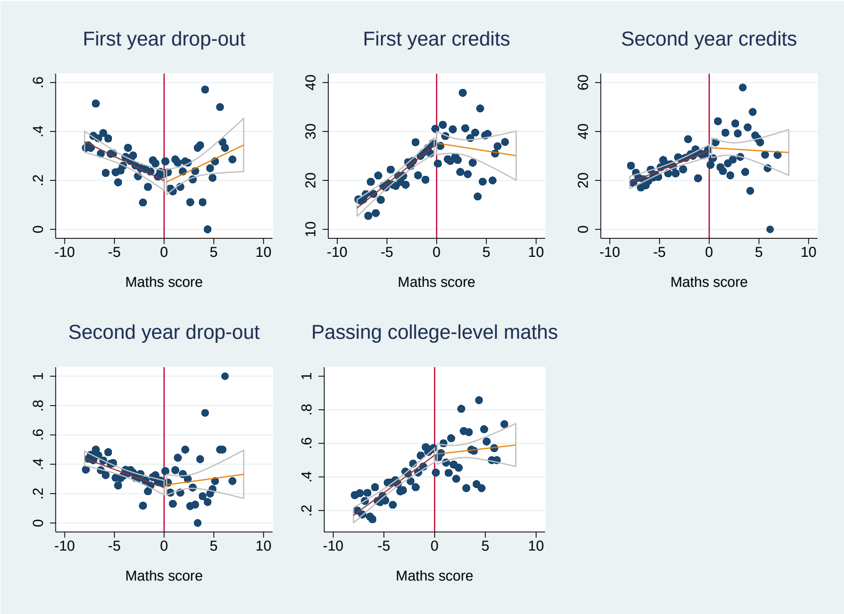
Note: the dots represent averages of the outcome variable, enrollment, computed for each value of the assignment variable (maths score). The lines correspond to linear fits of the dots, computed separately on each side of the cutoff for remediation assignment.

Table 6: Estimated discontinuities in the decision to enroll

	Local linear (±2)	Local linear (±1)	Local linear (±2.5)	Polynomial
No controls	-0.01	-0.06	-0.00	-0.01
	(0.05)	(0.08)	(0.05)	(0.04)
Cov.+Cohort FE	-0.01	-0.07	0.00	-0.01
	(0.05)	(0.08)	(0.05)	(0.04)
N	844	458	1,042	2,662
Sample mean	0.82	0.83	0.82	0.79

Note: in the second row I control for the high-school final grade, high-school province, type of high-school attended (general, vocational, etc.), gender, immigrant status; cohort fixed-effects are also included. The sample mean refers to the group of students who score within an interval with width h = 2, 1, 2.5 above the cutoff. Estimation methods: Local Linear Regression (LL) with bandwidth h = 2, 1, 2.5 in columns 2, 3, and 4; Polynomial regression with 2nd-order polynomial in column 5. Robust standards errors in parenthesis. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***.

Figure 5: Post-entry outcomes as a function of the assignment variable



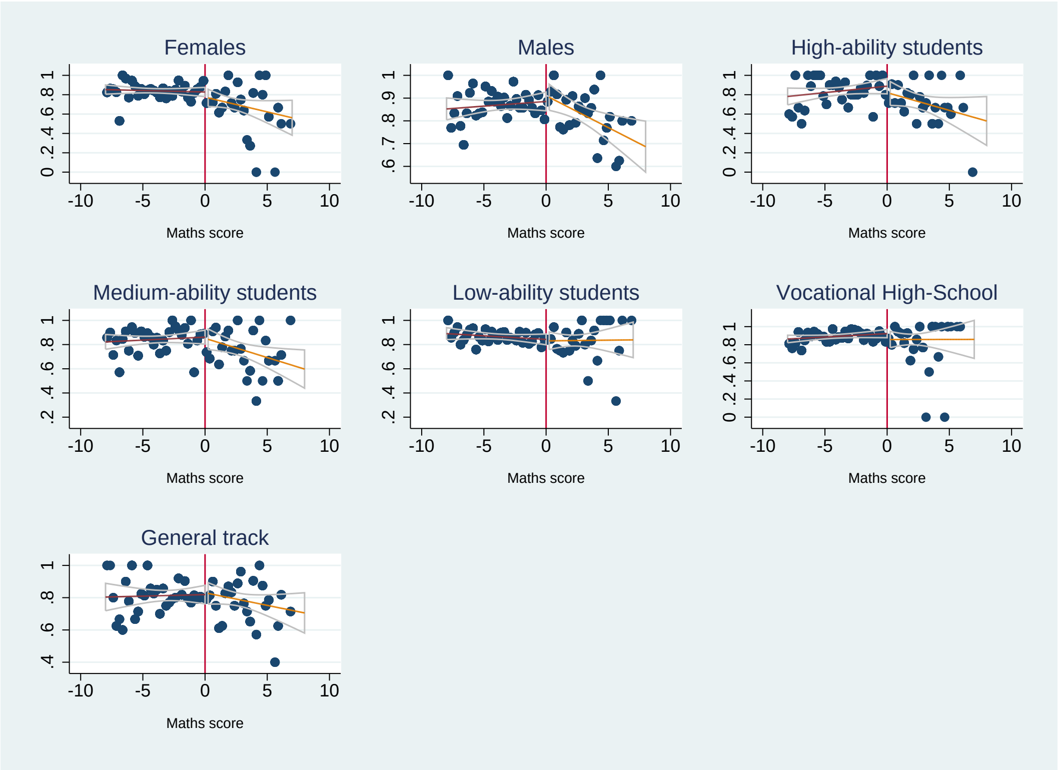
Note: the dots represent averages of the outcome variables, computed for each value of the assignment variable (maths score). The lines correspond to linear fits of the dots, computed separately on each side of the cutoff for remediation assignment.

Table 7: Estimated discontinuities in post-entry outcomes

	Local linear (±2)	Local linear (±1)	Local linear (±2.5)	Polynomial
1st year drop-out	0.05	0.05	0.03	0.02
	(0.06)	(0.08)	(0.05)	(0.05)
Sample mean	0.22	0.21	0.21	0.24
1st year credits	-2.29	-3.79	-0.67	-0.31
	(2.61)	(3.94)	(2.35)	(2.21)
Sample mean	27.44	28.13	27.92	27.20
Passing maths	-0.03	-0.06	0.03	0.03
	(0.07)	(0.10)	(0.06)	(0.05)
Sample mean	0.52	0.54	0.54	0.55
N	844	458	1,042	2,662
2nd year drop-out	0.13*	0.11	0.05	0.03
	(0.08)	(0.11)	(0.07)	(0.06)
Sample mean	0.29	0.25	0.27	0.28
2nd year credits	-5.62	-5.62	-2.28	1.32
	(4.23)	(6.14)	(3.79)	(3.52)
Sample mean	31.59	32.90	32.56	32.84
N	584	316	723	1,960

Note: the first column indicates the dependent variable. In all regressions I control for the high-school final grade, high-school province, type of high-school attended (general, vocational, etc.), gender, immigrant status; cohort fixed-effects are also included. The sample mean refers to the group of students who score within an interval with width h = 2, 1, 2.5 above the cutoff. Estimation methods: Local Linear Regression (LL) with bandwidth h = 2, 1, 2.5 in columns 2, 3, and 4; Polynomial regression with 2nd-order polynomial in column 5. Robust standards errors in parenthesis. Significance at the 10% level is represented by , at the 5% level by $*$, and at the 1% level by $**$.

Figure 6: Enrollment decision, for each subgroup, as a function of the assignment variable



Note: each graph represents the enrollment decision as a function of the assignment variable, for each subgroup considered. The dots represent averages of the dummy variable "enrollment", computed for each value of the assignment variable (maths score). The lines correspond to linear fits of the dots, computed separately on each side of the cutoff for remediation assignment

Table 8: Estimated discontinuities in the decision to enroll, by subgroup

	Local linear (±2)	Local linear (±1)	Local linear (±2.5)	Polynomial
Female	0.12	0.05	0.11	0.09
	(0.09)	(0.13)	(0.08)	(0.08)
N	352	205	440	1,265
Sample mean	0.75	0.73	0.75	0.71
Male	-0.12*	-0.19**	-0.09	-0.08
	(0.06)	(0.08)	(0.05)	(0.05)
N	492	253	602	1,397
Sample mean	0.87	0.91	0.87	0.84
High-ability	0.01	-0.17	0.01	-0.07
	(0.12)	(0.18)	(0.11)	(0.10)
N	153	80	191	477
Sample mean	0.81	0.83	0.81	0.73
Low-ability	-0.02	-0.11	-0.00	0.02
	(0.08)	(0.11)	(0.07)	(0.07)
N	389	203	482	1,206
Sample mean	0.82	0.83	0.82	0.83
Medium-ability	0.00	0.07	0.00	-0.02
	(0.09)	(0.16)	(0.08)	(0.08)
N	278	158	340	882
Sample mean	0.82	0.81	0.82	0.77
Vocational hs	-0.05	0.07	-0.03	-0.06
	(0.10)	(0.15)	(0.08)	(0.08)
N	269	131	331	1,072
Sample mean	0.86	0.90	0.86	0.86
General track	-0.01	-0.16	0.00	0.01
	(0.08)	(0.12)	(0.07)	(0.07)
N	401	221	493	982
Sample mean	0.79	0.79	0.79	0.79

Note: the first column indicates the subgroup considered. In all regressions I control for the high-school final grade, high-school province, type of high-school attended (general, vocational, etc.), gender, immigrant status; cohort fixed-effects are also included. The sample mean refers to the group of students who score within an interval with width h = 2, 1, 2.5 above the cutoff. Estimation methods: Local Linear Regression (LL) with bandwidth h = 2, 1, 2.5 in columns 2, 3, and 4; Polynomial regression with 2nd-order polynomial in column 5. Robust standards errors in parenthesis. Significance at the 10% level is represented by , at the 5% level by $*$, and at the 1% level by $**$.

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