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The effectiveness of remedial courses in Italy: a fuzzy regression discontinuity design

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Abstract Skills are important for many social and economic outcomes. Whereas interventions during childhood are considered crucial to increase the skills of disadvantaged individuals, in this paper, we try to understand whether interventions which take place later in life can also be effective. With this aim, we evaluate the effects on student achievement of a number of remedial courses provided by an Italian university. We use a *fuzzy regression discontinuity design* to identify the causal effect of remedial courses relying on the fact that students were assigned to the treatment if their performance in a placement test was below a certain cutoff point. We deal with partial compliance by using the assignment rule as an instrumental variable for the effective attendance to remedial courses. From our analysis, it emerges that students attending the remedial courses whose results were just below the cutoff point acquire a higher number of credits than students whose results were just above the cutoff. We also find that remedial courses reduce the probability of dropping out from an academic career.

Keywords Remedial courses · Tertiary education · Public policy · Fuzzy regression discontinuity design · Instrumental variables

JEL Classification I23 · I21 · I28 · C26 · J24

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1 Introduction

Tertiary education is increasingly important in shaping individual prospects in terms of income, employment opportunities, health, and even happiness, and represents a major driver of economic competitiveness and growth. Nevertheless, many individuals fail to acquire a college educational level. Policies aimed at increasing progression from high school to college and ensuring that students do not dropout from their educational programs are becoming crucial on national agendas (Riphahn and Schieferdecker 2012). Among the strategies aimed at increasing access to and persistence in tertiary education, one of the most commonly discussed is remediation.

Remedial courses are aimed at providing underprepared students with the skills necessary for a college education. These courses should allow the whole body of students to possess the minimum skills needed to undertake college-level courses and to address disparities generated in primary and secondary education.

Approximately one third of US university students are required to take remedial courses in basic skills such as reading, writing, or mathematics (Calcagno and Long 2010). While remediation represents an important feature of higher education in the USA, it is much less common in European countries. Nevertheless, an increasing number of European universities have recently started to offer remedial programs. For example, since the 2001 reform of the university system in Italy, universities have to test freshmen students' skills in relation to the requirements necessary for their chosen degree course, and universities should try to address any shortcomings. To this purpose, many Italian universities organize courses at a pre-university level at the beginning of each academic year so as to enable students to begin their university careers with an adequate level of competence.

Despite of their increasing application, remedial courses are controversial. Some opponents argue that they drain resources, both in terms of money and time, towards students who are ill-suited for college. Others claim that placement into remedial classes may negatively influence student outcomes due to social stigma and negative effects on self-esteem and educational expectations. Critics are also concerned about the significant costs of remediation and argue that taxpayers already pay for educational opportunities by financing secondary education. Finally, little is known about their effectiveness, since most colleges do not perform systematic evaluations of their programs.

Given the recent emphasis on policies of interventions during early childhood to increase skills and reduce inequality (Carneiro and Heckman 2003; Cunha and Heckman 2010; Anger and Heineck 2010; Silles 2011; Jürges et al. 2012), understanding the returns of remedial interventions is a very relevant issue. Both cognitive and noncognitive skills are crucial for an individual's life prospects both in terms of economic and social outcomes, such as economic success, health, family stability, and social interactions. These skills develop in early childhood, and public policies focused on early interventions can be particularly effective. However, in many contexts, older individuals may still need to increase their skills to achieve better results. Therefore, it seems worthwhile to make an effort to try to understand the effects of alternative policies taking place later in life.

Only a few works have attempted to evaluate the effects of remediation on students' academic performance or labor market outcomes. Estimating the impact of remedial courses is not straightforward as the assignment of students to these courses is not random. Typically, students are assigned to remedial courses in relation to some measure of their abilities, such as their secondary education curriculum. As a result, students of a lower ability are typically required to take remedial courses. This introduces a bias in those evaluations that try to measure the effectiveness of these courses by simply comparing the performance of participating students with the performance of students not involved in these programs. In fact, it is not sufficient to control for individual characteristics since the selection of students into the program is not only determined by observable variables (conditional independence assumption) but is also influenced by unobservable characteristics that might be related to the outcome, giving rise to endogeneity problems. For instance, not all the students who are required to take remedial courses follow them effectively. Problems of self-selection can lead both to an upward bias (for example, when only highly motivated students attend the courses) or to a downward bias (when courses are attended only by students with worse unobservable abilities) making it difficult to understand the effective impact of remediation on student achievement.

Some recent empirical studies have undertaken a variety of estimation strategies to handle these problems and to evaluate the effectiveness of remedial courses on outcomes such as performance in academic courses, probability of graduation, and labor market earnings. Bettinger and Long (2009) analyze the effect of remediation in Ohio by using an instrumental variable strategy, which relies on the importance of distance from university in a student's college choice combined with the fact that, in this State, the rules governing assignment to remedial classes differ across universities. They show that remedial classes produce beneficial effects: remedial students are more likely to persist in college and to complete their educational programs compared with students with similar characteristics who did not take these courses. Martorell and McFarlin (2011) and Calcagno and Long (2010) undertake an estimation strategy based on a regression discontinuity design (RDD) and exploit the fact that remedial placement in the States they consider, Texas and Florida, respectively, is decided on the basis of the score that students obtain in a placement exam. Martorell and McFarlin (2011) find that remediation has little effect on a wide range of educational and labor market outcomes, while Calcagno and Long (2010) find that remediation promotes early persistence at college but does not produce positive effects on degree completion and on the number of college credits acquired by students.[1]

In this paper, in following a similar approach to that used by Martorell and McFarlin (2011) and Calcagno and Long (2010), we present new evidence regarding the effects of remedial courses on the achievement of college students in Italy. To the best of our knowledge, there are no other works investigating the effects of remediation in European countries.[2]

We exploit data on about 4,000 freshmen students enrolled in the academic year 2009/2010 at the University of Calabria, a medium-sized Italian public university. Thanks to a project promoted by the regional government of Calabria and financed by the European Social Fund, students who were not considered ready to attend university courses were encouraged to take remedial classes aimed at improving their basic skills. The remedial courses, consisting of 160 h of lectures, were carried out at the beginning of the academic year and covered both mathematics and language skills. Assignment to remedial courses was based on the results obtained by the students at a placement test, and only students who, in each field of study, were placed below a certain score were advised to take remedial courses. Courses were strongly recommended but were not compulsory, and, as a consequence, compliance of students with the assignment rule was not perfect.

Thanks to the cutoff rule adopted to assign students to the treatment, it is possible to assess the effects of the program by using a fuzzy RDD and by considering the assigned treatment through the cutoff rule as an instrument for the effective attendance of remedial courses. Due to some randomness in the scores obtained at the placement test, students whose results placed them close to the cutoff point, whether above or below, are academically equivalent, and, therefore, any jump in the relationship linking academic performance to student placement test score close to the cutoff can be taken as evidence of a treatment effect.

We evaluate the effectiveness of remedial courses by considering some measures of student academic performance after 2 years of college: the number of credits earned by students, the probability of dropping out of the university, and the average grade obtained at passed exams.

After controlling for partial compliance, we find that treated students gain a higher number of credits than students who were just above the threshold and face a lower probability of dropping out from their academic careers. On

[1] A number of other papers have focused on remedial programs in compulsory education. For example, Jacob and Lefgren (2004), in investigating the effects on student achievement of remedial intervention implemented in Chicago public schools, show a positive effect on the academic achievement of third graders, but not of sixth graders. Lavy and Schlosser (2005) analyze the impact of remedial intervention for underperforming high school students in Israel and find a significant increase in the school enrollment rate of participating students.

[2] One exception is the study by Lagerlöf and Seltzer (2009) that analyzed the effects of remedial courses in Mathematics on the learning of Economics by using a small sample from a UK Department and found no positive effects.

the other hand, we do not find any statistically significant effect on the grades obtained at passed exams.

It is worth noticing that our analysis improves upon similar previous works in a number of ways. Firstly, as students were not allowed to retake the placement test, we do not have to deal with problems deriving from the fact that unobserved factors may influence the likelihood of achieving the remedial cutoff point after retesting. Secondly, since we have information on the exact number of hours of remedial courses attended by each student, we accurately measure the intensity of treatment and avoid problems that may derive from students who enroll on remedial courses but do not effectively attend the whole program. Finally, given the Italian institutional setting, remediation does not affect student choices in terms of field of study: students in our sample were required to choose their subject of study before the placement test and were not allowed to change this choice. In addition, the courses considered to evaluate students' performance were compulsory as students cannot choose courses during the first year of their degree program.

The paper is organized as follows. In Section 2, we provide some information on the Italian university system and describe the remedial program and the data used in the empirical investigation. Section 3 presents the estimation strategy adopted, provides some tests of the validity of RDD, and discusses estimation results. Section 4 concludes.

2 Background and descriptive statistics

The Italian university system is organized around three main levels: first-level degrees (legal duration of 3 years), second-level degrees (a further 2 years), and PhD degrees. In order to gain a first-level degree, students have to acquire a total of 180 credits. Students who have acquired a first-level degree can undertake a second-level degree (acquiring 120 more credits). After having accomplished their second-level degree, students can enroll onto a PhD degree.

Italian universities are required to test freshmen students' skills in relation to the requirements necessary for their chosen degree course. Students who do not meet a minimum required level of skills are invited to undertake educational processes which should enable them to start their academic courses with the adequate level of skills. In order to help students attain this level, at the beginning of each academic year, many Italian universities organize a number of courses at pre-university level, which typically focus on mathematics and language skills.

Notwithstanding the widespread adoption of remedial courses, their effectiveness has never been investigated. Such programs are often decided at faculty or department level, and it is difficult to get data on placement rules and on students' characteristics and outcomes.

In this work, we take advantage of a project, financed by the European Social Fund, involving 4,019 students who were enrolled in the academic year

2009–2010 at the University of Calabria, a medium-sized public university located in the south of Italy. The project was aimed at improving students' basic competences through an intensive training program offering a number of courses in subjects such as mathematics and language skills. Students who participated in the project were asked to take a placement test (with multiple choice questions) before the start of the educational activities (in September 2009). Students were tested to determine whether they were able to meet a given level of academic proficiency that was defined autonomously by each field of study. We have data on five different fields of study offered at the University of Calabria: Economics (31% of students), Pharmacy (15%), Humanities (24%), Mathematics and Natural Sciences (15%), and Political Sciences (15%).[3] In each field of study, students whose result was below a certain cutoff score (defined in terms of the percentage of questions that were answered correctly) were strongly advised to enroll on the remedial courses. Students attending the courses were required to sign an attendance form.

We build a variable, *test score*$_i$, as the percentage of correct answers given by student i in the placement test, and we subtract the threshold level fixed by each faculty to assign students to remediation so as to make students' scores across different fields of study homogeneous. In this way, a score of $+1$ indicates that the student is placed just above the threshold and he/she is not invited to attend the remedial courses, while a score of 0 or a negative score indicates that the student is below the threshold and advised to attend the remedial courses. We define the dummy variable *assigned treatment*$_i$, which takes the value of one if student i has been assigned to the remedial courses (test score$_i \leq 0$) and zero otherwise.

There was a placement test which students were not allowed to retake. As a consequence, unlike other studies examining remedial courses in the USA, we do not have to deal with problems deriving from the fact that unobserved factors may influence the likelihood of achieving the remedial cutoff point after retesting.

Remedial courses began in the first week of September 2009 and lasted about 2 months for a total of 160 teaching hours covering mathematical and language skills. It is worth noting that a standard college-level course typically consists of 60 h, meaning that the investment in remedial teaching activities and student time was considerable. It was strongly suggested that students assigned to treatment attended the courses, but attendance was not compulsory.

We build the variable *effective treatment*$_i$ as the number of hours of remedial courses attended by student i. This variable has a value of zero just for those students who decided not to bother with remedial courses. An attendance form was signed at the end of each class, and the data were collected from

[3] We have decided to exclude students enrolled in Engineering from our analysis because all the students in this field, independently of their test score obtained, were encouraged to attend the remedial courses.

the university administrative office. For each student, we have known exactly which classes were attended and for how many hours.

As remedial courses were quite intensive and time-consuming, we do not expect students to have attended additional training activities, and, as a consequence, any possible improvement in their academic performance can be reasonably imputed to the remedial program. On the other hand, students who did not attend the program were not supposed to engage in alternative educational processes as remedial courses were not a prerequisite to enrolling on college-level courses. We can reasonably argue that students who did not attend the remedial courses did not attend alternative educational programs: remedial courses were free and sponsored by the university, while alternative programs did not have such characteristics and, as a consequence, were much less attractive.

Remedial courses do not confer academic credits. Regular college courses for all students only started after the remedial courses had ended.

Thanks to the administrative data provided by the University of Calabria, we have detailed information on all the students enrolled at the University of Calabria in the academic year 2009–2010. We observe a number of individual characteristics such as gender, province of residence, year of high school completion, and some measures of ability (*high school grade* and type of *high school* attended).

As shown in Table 1, which reports descriptive statistics for the whole sample and for treated and control students, respectively, 60.8% of students were assigned to remedial courses (assigned treatment). However, participation in the treatment was only partial. The average number of hours of remedial courses attended by students assigned to the treatment was 81 (out of 160),

Table 1 Descriptive statistics

Variable	All		Treated		Control	
	Mean	SD	Mean	SD	Mean	SD
Assigned treatment	0.608	0.488	1	0	0	0
Effective treatment	49.813	62.553	81.020	61.940	1.438	13.469
Treatment: 80% of hours	0.342	0.474	0.557	0.497	0.009	0.094
Test score	−1.978	14.796	−11.387	8.748	12.608	9.466
Credits	46.369	38.759	40.074	36.487	56.126	40.145
Dropout	0.237	0.426	0.261	0.439	0.201	0.401
Average grade	23.931	2.710	23.193	2.529	24.974	2.614
Female	0.647	0.478	0.680	0.466	0.596	0.491
High school grade	81.586	11.616	79.022	11.122	85.560	11.245
Lyceum	0.487	0.500	0.410	0.492	0.608	0.488
Late enrollment	0.238	0.426	0.252	0.434	0.216	0.412
Field: economics	0.307	0.461	0.315	0.464	0.296	0.456
Field: pharmacy	0.152	0.359	0.187	0.390	0.098	0.297
Field: humanities	0.239	0.427	0.187	0.390	0.319	0.466
Field: maths and sciences	0.150	0.357	0.137	0.344	0.169	0.375
Field: political sciences	0.152	0.359	0.173	0.379	0.118	0.323
Obs.	4,019		2,443		1,576	

while the average of effective treatment for the whole sample is equal to 49.8. Only about 34% of the sample (55% of treated students and 0.9% of control students) participated in at least 80% of the total amount of lectures (in terms of hours) provided as part of the remedial program (*treatment: 80% of hours*).

Females made up about 65% of the sample; high school grade, ranging from 60 to 100, is on average at 82 (79 and 85.6, respectively, for treated and controls); 49% of students attended a *lyceum* (rather than a technical or vocational school), and about 24% of them did not enroll at the university in the same year as they had graduated from high school (*late enrollment*).

By the end of the second year of their degree program, students had acquired about 46.3 credits (out of the 120 that they were expected to achieve), and 23.7% of them had dropped out or were at a strong risk of dropping out since they had acquired zero credits (see below). Exams are evaluated on a scale ranging from 18 (the minimum pass mark) to 30 cum laude (set equal to 31), and the average grade at passed exams was 23.9.

3 The effects of remedial courses on student achievement through a fuzzy regression discontinuity design

To recover the causal effect of remedial courses on student performance, we use a fuzzy regression discontinuity design exploiting the fact that the assignment to the treatment has been defined as a discontinuous function of the student's placement test score (a student is assigned to remedial courses if his/her test score is zero or below). Even if the test score is correlated to student academic achievement, the relationship should be smooth with no jump in the proximity of the cutoff point.

Meanwhile, in the *sharp* regression discontinuity design, treatment is defined deterministically by the fact that the forcing variable is below or above a certain threshold; hence, compliance of students to the assignment was not perfect in our context. On the one hand, some of the subjects assigned to the treatment decided not to participate in the educational program ("no-shows") while, on the other hand, few students who were assigned to the "control group" (that is, they were not advised to take remedial courses as their test score was above the threshold) moved into the treatment group by deciding to attend the remedial courses. Therefore, since the effective participation in the remedial courses is potentially related to observable and unobservable determinants of students' achievement, the estimates might be inconsistent.

To deal with endogeneity problems arising from partial compliance, as is standard in the literature, we follow an *instrumental variable* estimation strategy by using the exogenous assignment to the treatment as an instrument for effective participation in the remedial courses. Therefore, we use a fuzzy regression discontinuity design in which the treatment status is probabilistically determined as a discontinuous function of the test score (Lee and Lemieux 2010; Angrist and Pischke 2009). Following most of the papers in the literature, we use a parametric approach.

Formally, we estimate the following model:

$$Y_i = \beta_0 + \beta_1 \text{ effective treatment}_i + \beta_2 f\,(\text{test score}_i) + \beta_3 X_i + \mu_k + \varepsilon_i \qquad (1)$$

$$\text{effective treatment}_i = \varphi_0 + \varphi_1 \text{ assigned treatment}_i$$
$$+ \varphi_2 g\,(\text{test score}_i) + \varphi_3 X_i + \mu_k + \upsilon_i \qquad (2)$$

where Y_i is the performance of student i (measured as the number of credits earned, the probability of dropping out, and the average grade at exams); as explained in Section 2, effective treatment is a variable measuring the number of hours of remedial courses attended (in some specifications we use, alternatively, a dummy variable taking the value of one when the student has attended at least 80% of the hours of the remedial courses); $f(\text{test score}_i)$ and $g(\text{test score}_i)$ are two flexible functional forms relating test score, respectively, to academic outcomes and participation to effective treatment; X_i is a vector of individual characteristics (gender, high school grade, lyceum, province of residence, late enrollment), which we use to increase the precision of estimates; μ_k are field dummies to take any difference across fields into account; and ε_i and υ_i are random error terms.

In order not to impose any restriction on the underlying conditional forms, we include among controls interaction terms between the polynomial terms of test score and effective treatment and use as instrumental variables assigned treatment and the interactions between the latter and $g(\text{test score}_i)$. This procedure corresponds to estimating separate functions on either side of the cutoff point.

Equation 2 represents the first stage of the relationship between the student's effective participation in remedial courses and the score obtained at the placement test. The parameter ϕ_1 is the effect of the assigned treatment on the effective participation in the remedial courses.

Equation 1 shows that student achievement is related to test score, since students with higher abilities tend to perform well both at the placement test and in their following academic activities. However, the relationship between test score and academic achievement can be estimated by using a smooth function. Under the assumption that the relationship between the outcome variable and test score is continuous in a neighborhood of the cutoff point, any jump in the dependent variable in proximity to the cutoff point can be interpreted as evidence of a treatment effect. Therefore, the parameter β_1 measures the causal impact of remedial courses on student performance.

In what follows we will firstly discuss the main assumptions on which our estimation strategy relies and then present our main results.

3.1 Checks for random assignment around the discontinuity

The crucial assumption underlying the RDD approach is that unobservable characteristics do not vary discontinuously around the cutoff point, and the cutoff rule provides exogenous variations in the treatment "as good as a randomized experiment."

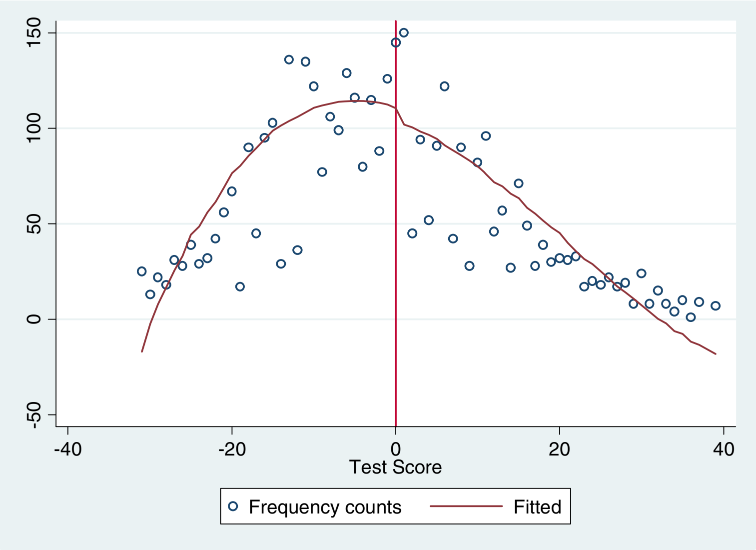

Fig. 1 Density of the forcing variable (test score)

This could not be the case if students behaved in such a way as to change their score when it was near the cutoff point. For example, students may purposely miss many test questions because they want to attend the remedial course or, alternatively, they may retake the placement test in order to obtain a better result and avoid the remedial courses. However, in our case, since students do not know what the threshold level necessary to pass the test is in advance, it is unlikely that they are able to marginally change their score near the cutoff point. Moreover, students were not allowed to retake the placement test. Therefore, the requirement that individuals must not have precise control over the assignment variable seems satisfied.

We carried out the formal test proposed by McCrary (2008) to investigate whether there is any discontinuity in the density of the assignment variable around the cutoff point. We followed the procedure implemented by Nichols (2007). The difference between the frequency to the right and to the left of the threshold is not statistically significant, the point estimates being −0.007 (s.e. 0.038). As a consequence, we fail to reject the null hypothesis that the jump in the density of test score at the threshold is zero.[4]

[4] Alternatively, the variable test score has been partitioned into equally spaced bins (of width 1); the frequency counts have been used as a dependent variable in a regression with a polynomial of test score (until the fourth order) and in a local linear regression. The variable assigned treatment is never statistically significant in these regressions, confirming the inexistence of a discontinuity at the cutoff point.

The absence of manipulation is confirmed by inspection of the graph below representing the density of the test score obtained by students at the placement test along with predicted values from a third-order polynomial model (Fig. 1). Since there is no discontinuity in the distribution of the test score at the cutoff point, we are reassured that this variable was not manipulated by the students.

An additional requirement for the validity of RDD is that predetermined covariates for students just above and below the cutoff point should balance. In fact, in the absence of manipulation, students around the threshold score should not differ significantly in terms of observable and unobservable variables.

To investigate this issue, we run a number of discontinuity regressions using our baseline covariates, in turn, as a dependent variable, that is, we regress *female*, high school grade, lyceum, late enrollment on the dummy assigned treatment and control for test score, and field of study dummies. The estimation results are reported in Table 2. In column 1, we show that the probability of observing a female student does not change sharply at the cutoff point. Similarly, assigned treatment does not produce any statistically significant effect on high school grade. On the other hand, we find that the probability of having attended a lyceum is not a smooth function of test scores and changes sharply at the cutoff point. Finally, the variable late enrollment does not show any jump at the cutoff point.

These results reassure us about the random assignment around the discontinuity point (Imbens and Lemieux 2008). However, since not all variables are balanced, we control for these variables in the regressions to avoid any bias due to the lack of balance.

3.2 First-stage results

As explained above, in our setting, assignment to the treatment, on the grounds of whether student performance was below a predetermined threshold, does not perfectly predict actual participation in remedial courses.

Based on the *first-stage equation*, in Figs. 2 and 3, respectively, we plot the number of hours of remedial courses attended (effective treatment) and the probability of attending at least 80% of the remedial courses (treatment: 80% of course hours) against the score obtained by students at the placement test.

In Fig. 2, the circles are the means of the hours effectively attended for a given test score, while the connected points are the predicted values from the

Table 2 Differences in predetermined characteristics. RDD estimates

	(1) Female	(2) High school grade	(3) Lyceum	(4) Late enrollment
Assigned treatment	0.015 (0.028)	−0.129 (0.658)	0.095* (0.030)	−0.012 (0.026)
Observations	4,019	4,019	4,019	4,019

*$p = 0.05$ (statistically significant)

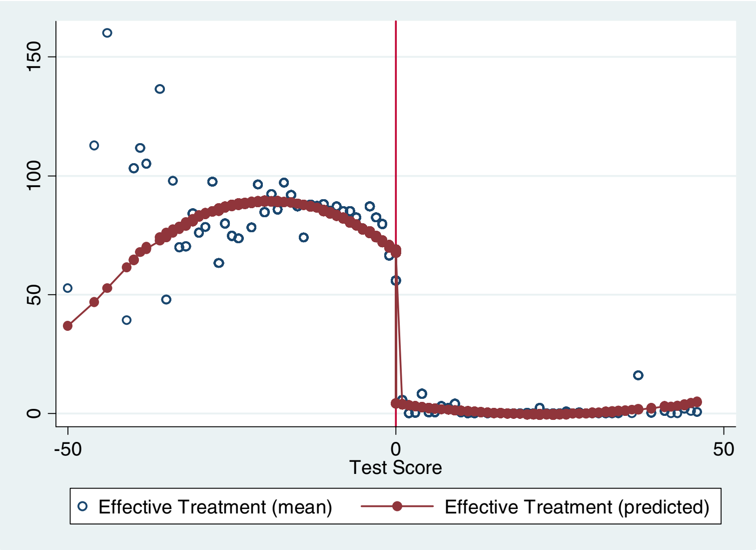

Fig. 2 First-stage relationship: test score and predicted hours of remedial courses

first-stage equation. As it is possible to see on the left-hand side of the graph in Fig. 2, students below the cutoff point attended an average of 81 course hours, while those above the cutoff point attended only 1.43 h. Similarly, Fig. 3 shows that the probability of attending at least 80% of the remedial activities

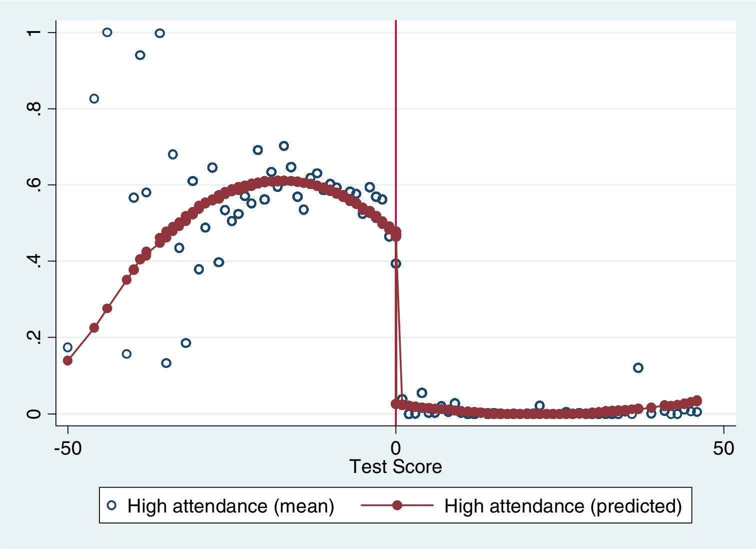

Fig. 3 First-stage relationship: test score and predicted probability of 80% of attendance

for those who scored below the cutoff point is 0.56, while it drops to just 0.01 for students who obtained scores above the threshold.

These graphs demonstrate the essence of the fuzzy regression discontinuity design we adopt to estimate the effects of remedial courses, since the discontinuous relationship between test scores and effective participation in remedial courses emerges clearly. Even though not all the students with scores below the cutoff point attended the remedial courses, their probability of attendance is significantly higher than that of students who scored above the cutoff point.

Due to the fact that the probability of treatment changes discontinuously at the cutoff point, it is possible to determine the treatment effect in the case of partial compliance by comparing mean outcomes of individuals in a narrow range on either side of the cutoff point and scaling the difference in outcomes by the difference in the probability of treatment.

3.3 Estimation results

In this section, we present our main results regarding the effects of remedial courses on student achievement. We use different measures of student performance as outcome variables. We focus on the number of credits obtained during the first 2 years of a degree program and on the probability of dropping out, but we also provide evidence of the effects of remediation on the average grade at exams.[5]

Two-stage least squares (TSLS) estimates are shown in Table 3 considering the number of *credits* acquired by students as a dependent variable. First-stage estimation results are reported in panel B of the table. Standard errors are robust to heteroskedasticity and allowing for clustering at the test score level to account for additional sampling errors arising with a discrete running variable (Lee and Card 2008).

To interpret the coefficients on the effective treatment better, we rescale the latter by dividing by 100. In this way, the effect of the treatment can be interpreted as the impact of attending 100 h (approximately the average number of hours of remedial course attended by students with positive remedial hours).

In order to choose a correct specification of $f(\text{test score}_i)$ and $g(\text{test score}_i)$, we visually inspect the data, and a quadratic or cubic specification generally provides a good fit. Then, in the estimates reported in the tables, we use polynomial trends from the first to the third order. However, results do not change when using higher order polynomials (estimates are not reported but are available upon request). We have also experimented by using some specifications in which we do not allow for different functional forms on either side of the cutoff point. Estimates of our parameter of interest turn out to be similar to those presented in the paper (not reported).

[5] Unfortunately, we do not have information on long-term outcomes, such as the probability of obtaining a degree or labor market outcomes.

Table 3 Fuzzy regression discontinuity estimates of remedial courses impact on credits. TSLS estimates. Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: two-stage least squares estimates							
Effective treatment	6.4626*	7.2951**	8.2096**	13.5369***	10.1467***	13.8624***	19.7968***
	(3.9042)	(2.9726)	(3.3818)	(4.5755)	(3.1636)	(4.3193)	(4.7709)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Interaction terms	No	Yes	Yes	Yes	No	No	No
Polynomial of test score	First	First	Second	Third	First	First	First
Window	Whole	Whole	Whole	Whole	−10/ + 10	−7/ + 7	−5/ + 5
Observations	4,019	4,019	4,019	4,019	2,055	1,521	1,178
Panel B: first stage							
Assigned treatment	0.513***	0.535***	0.461***	0.453***	0.548***	0.510***	0.498***
	(0.067)	(0.051)	(0.046)	(0.033)	(0.091)	(0.086)	(0.076)
R-squared	0.272	0.341	0.344	0.344	0.388	0.365	0.337
First-stage F-statistics	58.495	109.875	101.376	188.417	36.404	35.502	43.412
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel C: intention-to-treat effects							
Assigned treatment	4.4709*	4.9626***	5.2446***	6.9377***	5.5577***	7.0722***	9.8545***
	(2.4814)	(1.8765)	(1.9346)	(1.6813)	(1.6387)	(1.9456)	(2.6197)

The table reports IV estimates. The dependent variable is credits. In all regressions, we control for female, high school grade, lyceum, late enrollment, field of studies, and province dummies. Standard errors (reported in parentheses) are corrected for heteroskedasticity and allowing for clustering at test score level

$^{*}p = 0.1$; $^{**}p = 0.05$; $^{***}p = 0.01$ (statistically significant)

The first stage confirms that, controlling for flexible functions of test score, the assigned treatment strongly determines the effective treatment: around the threshold, being assigned to the treatment leads to about 46–54 more hours of remedial courses (the first-stage F-statistics is always higher than 500).

Considering the two-stage least squares estimates, in column 1 in which we do not control for individual covariates and we consider a linear function of test score, we find that having attended 100 h of remedial courses leads to an average of about 6.4 more credits and this effect is statistically significant at the 10% level. Adding individual covariates and field of study dummies among controls and controlling for a polynomial of test score (columns 2, 3 and 4) lead to more precise estimates: it emerges that the effect of remedial courses is positive and statistically significant at the 1 or 5% level. Participation in 100 h of remedial courses leads to an increase in the number of credits gained over the first 2 years ranging from 7.29 to 13.54 according to the polynomial form used. The estimated coefficient represents the average effect of remedial courses on those individuals who received treatment because they scored just below the cutoff point in the placement test (local average treatment effect).

As expected, test score correlates positively and strongly with subsequent student performance (not reported). The effects of control variables (not reported) are consistent with the findings emerging from the literature. Students with a higher high school grade obtain a much better academic performance. In addition, students who attended a lyceum perform better than students who come from *technical* or *vocational schools*. The dummy female is always positive and statistically significant.

As a robustness check, we present estimation results in columns 5, 6, and 7 that were obtained by using a local linear regression approach and considering just those observations in a neighborhood around the discontinuity (Angrist and Pischke 2009; Lee and Lemieux 2010). The comparison of average outcomes in a small enough neighborhood to the left and to the right of the threshold value should give an estimate of the effect of interest in a way that does not depend on the correct specification of the model for the conditional expected function.

Using the cross-validation procedure suggested by Lee and Lemieux (2010) to choose the optimal bandwidth, it emerges that the cross-validation function declines initially, but it becomes fairly flat after about 10 points of test score. Therefore, we experiment by focusing on three different bandwidths considering, respectively, students with a score ranging from −10 to +10, −7/+7, and −5/+5 points around the cutoff point. Following the literature, we only use a linear function of test score when dealing with these narrow windows instead of higher order polynomials.

Very similar results are obtained when we measure effective treatment with the dummy variable that has the value of one for students who attend at least 80% of remedial course hours (132 h). Having attended the 80% of the remedial activities leads to an increase ranging from 8.67 to 19.49 in the number of credits acquired (not reported).

As the policy maker is usually more interested in knowing about the expected benefits of the program to those students it targets, we report the intention-to-treat (ITT) effects in panel C of Table 3 (Heckman et al. 1999). To recover the ITT effects, we use a sharp regression discontinuity design in which the treatment status is simply defined by the placement rule (Imbens and Lemieux 2008; Angrist and Pischke 2009), which corresponds to the reduced form of our model (Eqs. 1 and 2). The estimates show that being assigned to the treatment, 160 h of teaching activities leads to an increase of between 4.47 and 9.85 credits. To compare this figure with the local average treatment effect, consider that the assignment to a remedial course of 100 h would determine an increase of between 2.79 and 6.16 in student credits according to the specification considered.

These estimates suggest that remedial course have positive effects on the number of credits acquired by students. The effect is not particularly large, but it has to be considered that the average number of credits acquired by students in 2 years (46.3) is also quite small.

It might also be the case that the remedial program has had a larger impact on those students who are most in need of support. To investigate this aspect, instead of considering the number of credits gained as a measure of performance, we focus on the probability of dropping out from the university. Although we do not have direct information on whether students have decided to drop out of their university studies, we consider students who have not passed any exam over the first 2 years of their degree program as students who have dropped out or who are at strong risk of dropping out. Then, we use this information to define a dummy variable, *dropout*, that takes the value of one when the student has not passed any regular exam over the first and the second years of his/her academic career and 0 otherwise.

For the sake of simplicity, we estimate a linear probability model for dropout (estimation results are in Table 4), repeating the specifications reported in Table 3. The first stage is identical to the estimation in Table 3 and is not reported. It emerges from TSLS estimates (columns 1, 2, 3, and 4) that students attending 100 h of remedial courses have a lower probability of dropping out of between 6 and 13.5 percentage points, statistically significant at the 10% level in the specification without controls and at the 5% level in all other specifications. Since the probability of dropping out for our sample students is of about 24%, the remedial program effect implies a reduction in the dropout probability of about 25–54%.

Results from local linear regressions are reported in columns 5, 6, and 7. The estimates barely change in terms of statistical significance but become larger in magnitude at increasingly narrow windows. In all specifications, remedial courses produce a reduction in the probability of dropping out from university studies.

The intention-to-treat effect (shown in the second panel of Table 4) is, as expected, smaller but still very relevant. Assignment to the treatment leads to a reduction in the probability of dropping out of between 4.43 and 10.08 percentage points or, equivalently, being assigned to a course of 100 h leads to a reduction in dropout probability of from 2.77 to 6.30 percentage points.

Table 4 Fuzzy regression discontinuity estimates of remedial courses impact on dropping out. TSLS estimates. Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Two-stage least squares estimates							
Effective treatment	−0.0629*	−0.0730**	−0.0914**	−0.1347*	−0.0840**	−0.1186**	−0.2025***
	(0.0360)	(0.0301)	(0.0445)	(0.0747)	(0.0367)	(0.0519)	(0.0689)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Polynomial of test score	First	First	Second	Third	First	First	First
Window	Whole	Whole	Whole	Whole	−10/ + 10	−7/ + 7	−5/ + 5
Intention-to-treat effects							
Assigned treatment	−0.0443*	−0.0506***	−0.0577**	−0.0684**	−0.0460**	−0.0605**	−0.1008***
	(0.0238)	(0.0170)	(0.0221)	(0.0267)	(0.0180)	(0.0215)	(0.0317)
Observations	4,019	4,019	4,019	4,019	2,055	1,521	1,178

The table reports IV estimates. The dependent variable is drop-out. In all regressions, we control for female, high school grade, lyceum, late enrollment, field of studies and province dummies. Standard errors (reported in parentheses) are corrected for heteroskedasticity and allowing for clustering at test score level

$^{*}p = 0.1$; $^{**}p = 0.05$; $^{***}p = 0.01$ (statistically significant)

We have also investigated whether the reduction in dropout probability occurs mainly during the first year or, to some extent, during the second year of academic career. The large majority of students (99%) who have not passed any exams during their first year tend to repeat this behavior in their second year and, therefore, looking at students who have not passed any exams during their first year does not provide any additional insights beyond what we have learned from previous estimates. Therefore, we focus on those students who passed some exams during their first year but were unable to pass any additional exams during their second year. We find that having attended remedial courses does not produce any statistically significant effect on dropout behavior during the second year, suggesting that the effects of remediation are concentrated at the beginning of a student's academic career.

One of the main advantages of the regression discontinuity design is that it allows visual identification of the treatment effect. In Fig. 4 (panel a, credits; panel b, dropout), we show the intention-to-treat effects, which are more relevant from a policy point of view. The circles represent the means of the dependent variables for students with a given test score level. In the figure, the predicted values are presented from a model explaining credits and dropout probability in relation to the assigned treatment, controlling for a quadratic function of test score (specification 3 in Tables 3 and 4, respectively). We focus on a window of −20/+20. The vertical line at the value of zero of the test score denotes the cutoff point defined by the assignment rule.

In panel a of Fig. 4, a jump emerges in the relationship between the credits and the test score in the proximity of the cutoff point: students assigned to the treatment (just below the cutoff point) earn more credits than students just above the cutoff point. Although the jump is statistically significant, it is not very large in magnitude: about 5.24 credits more for students assigned to the treatment (corresponding to about 0.13 standard deviations of credits).

The jump is also quite clear when inspecting the conditional mean of dropping out probability around the cutoff point (panel b). As shown above, the impact of remedial courses on this outcome variable is larger, suggesting that remedial courses have a positive effect, especially on the students most in need of help.

Finally, we investigate whether remedial courses have any impact on the average grade students obtained in the exams they passed. In our sample, 3,013 students passed at least one exam in the 2 years considered, and it is possible to calculate the average grade for them. We estimate the same specifications as in Table 3. We do not find any statistically significant effect of remedial courses on the average grade at exams when controlling for different polynomial orders of test score (not reported).

A possible explanation is that remedial courses, as shown above, allow a larger number of students to pass exams, and this positive effect appears to be stronger for low-ability students at risk of dropping out. Students pass the exam when they reach the minimum pass line (18), and since the remedial program has increased the number of students reaching the line, this translates into a reduction in the average grade obtained in exams.

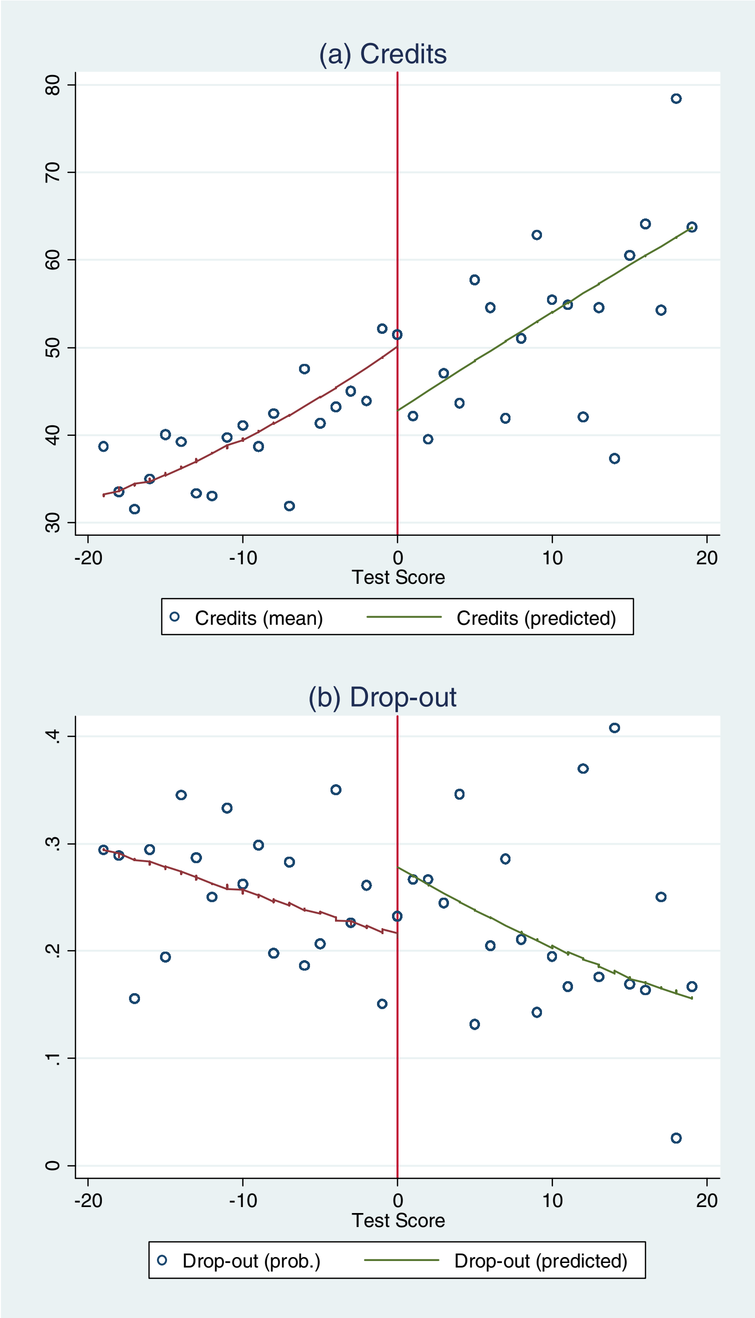

Fig. 4 Intention-to-treat effects. **a** Credits and test score. **b** Probability of dropout and test score

4 Concluding remarks

While remedial courses are increasingly used by European universities, little is known about their effects. Only recently a small literature on this topic has been trying to handle, with adequate estimation strategies, the endogeneity problems that undermined the earlier evidence. These recent studies are all focused on the US experience, and it is difficult to understand how the effects found are related to the specific features of the US educational system.

In this paper, we have tried to shed some light on this issue by providing an evaluation of remedial courses offered by an Italian university. To uncover the effects of these remedial courses, we have used a fuzzy regression discontinuity design relying on the fact that only students scoring below a certain threshold at a placement test value were advised to attend the remedial program.

Compared to similar works investigating the effects of remedial courses in the USA, we take advantage of the fact that, in our case, remedial courses are not prerequisites for enrollment into college-level courses, and students did not have any incentive to try to avoid being placed under remediation. Moreover, students could not retake the placement test and, as a consequence, we did not face manipulation problems. Another interesting feature of our analysis is that we can measure the intensity of the treatment rather precisely, as we know the exact number of lesson hours each student was present at.

It emerges from our analysis that remedial courses have a positive impact on the number of credits acquired by students during the first 2 years of their academic career. The magnitude of the effect, ranging from seven to ten credits in most specifications, is not very large if one considers the relevant investment of 160 h in terms of teaching activities (and students' effort).

However, we find significantly larger effects with regard the probability of dropouts from the university: a reduction of 7–8 percentage points for students attending remedial courses (a decrease of about 30%), suggesting that remedial courses could have an impact especially on low-ability students.

Our results, suggesting that educational interventions later in life can be effective in helping individuals attain high levels of education, are in contrast with those emerging from studies analyzing the effect of remedial courses in the USA, which typically find very small or null effects. The positive impact we find may be related to the fact that while remediation in the USA mainly attracts underprepared students of low socioeconomic status, in Italy, just as in many other European countries, remediation is aimed at filling deficits deriving from differences between secondary educational programs (tracking between professional and more academically orientated schools is a typical feature of many European educational systems). It could be that remediation is able to bridge this kind of gap, but it may also be less effective in filling deficits deriving from poor family background.

It is also important to consider that the policy we have analyzed was quite expensive (about 1,000 Euros per student), as courses were organized into small classes (fewer than 40 students per class), teaching activity was very intensive and each professor was supported by an assistant. A crucial issue is whether the positive effects of the policy can justify its costs in comparison to other feasible alternatives. As emerged from De Paola et al. (2012) when focusing on a sample of students enrolled at the same university as the one considered in this study, an improvement in student performance can be obtained at a much lower cost through the provision of financial incentives. However, the benefits of monetary incentive were mainly concentrated among students of higher ability. Little is known, instead, about the effects of alternative polices to help lesser skilled students enter a university and complete their studies. Additional research is necessary to understand whether remediation is a cost-effective investment.

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