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ABSTRACT

The Long-Run Effects of College Remedial Education

We investigate the long-run impact of college remedial education on students' academic performance and employment status. By implementing a Fuzzy Regression Discontinuity Design we show that attending remedial courses positively affects the probability to get a university degree, whereas no significant effect is found on labour market outcomes.

JEL Classification: I23, I28, C26

Keywords: remediation, education, employment, RDD

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1. Introduction

Remediation is the most common approach used by colleges to support students with fragile academic abilities. Nevertheless, the literature offers contradictory evidence on the costs and benefits related to remedial education (see, among others, Duchini, 2017; García-Pérez and Hidalgo-Hidalgo, 2017), and remediation effects on human capital of low-skilled individuals are still debated by both academics and policy-makers.

Our paper provides some elements of novelty into the discussion on remedial education. First, we focus on non-mandatory assignment to remedial courses, different from most of the studies conducted in the US (Boylan *et al*., 2017). Second, albeit the literature largely concentrated on the short-run effects of remediation (see Calcagno and Long, 2008), this research covers a 10-year horizon after remedial courses are provided, which allows us to analyse not only students' academic performance (Zeidenberg *et al*., 2007) but also labour market outcomes in the long-run.

In fact, only a few works considered the link between labour market and remediation, coming up with conflicting results. Lavy *et al.* (2018), by using nearest-neighbour and kernel matching techniques, find a positive effect of school remediation on employment. Conversely, Martorell and Mc-Farlin (2011), in analysing college remediation through a RDD, do not detect any significant impact on earnings.

Our analysis investigates how remediation, introduced at the beginning of the college career, affects the probability of graduating, the probability to be employed and the years needed to find a job after graduation. The short-run impact of these remedial courses has been studied by De Paola and Scoppa (2014) to whom we refer for a detailed description.

To analyse whether the remedial program affects academic and labour market outcomes, we adopt a Fuzzy Regression Discontinuity Design exploiting the fact that students were assigned to remedial courses if their score on a placement test was below a certain threshold, and that compliance was not perfect. Our results show that remediation positively affects the probability of graduating and of obtaining a degree within a reasonable timeframe, whereas we do not find any impact on the probability of employment and on other related labour market outcomes.

2. Background

The remedial courses under scrutiny involved 3,955 freshmen students who enrolled in the 2009/2010 academic year at the University of Calabria in Italy. The program consisted in lectures delivered over 2 months for a total of 160 hours covering topics in both mathematics and language. Students were asked to take a placement test before the start of the academic year in order to assess their level of academic proficiency. Assignment to remediation was based on the placement test score and only students who scored below a certain threshold, set by each Degree Course, were advised to take remedial lectures. Therefore, the courses were not compulsory, but highly recommended, and compliance with the assignment rule was not perfect.

The data on students' career is provided by the University of Calabria and contains information about a number of individual characteristics, i.e. age, gender, type of school attended, field of study and high-school grade.

We exploit information about students' performance to build our educational outcomes and create the following variables: *Graduation* measures the probability of graduating; *Graduation on time* is a dummy variable taking the value 1 when the student has completed the degree within three (bachelor) or two (master) years and 0 otherwise; *Graduation within one year* takes the value 1 when no more than one additional year was required to graduate and 0 otherwise; *Graduation mark* is the final grade ranging between 66 and 110, and *Graduation delay* is the number of additional years needed to graduate.

Regarding the labour market outcomes, we use two different data sources. First, AlmaLaurea[1] provides data on graduates who are interviewed one year after the degree is taken (1,886 students in our sample), and accordingly we build the dummy variable *Employed after one year.* Second, we carried out phone interviews, ten years after the remedial courses were provided, involving a randomly-selected sample of 1,200 students, regardless of whether they have completed their studies. Through phone interviews we collected information about the employment status to build two dummies taking the value 1, respectively, if the respondent had a job at the time of the interview (*Currently employed)* or if she has worked in the past (*Employed in the past*) and 0 otherwise, and a variable that indicates the number of years needed to find a job after graduation (*Years to find a job*).

3. Methodology

To recover the impact of remediation on educational and labour market outcomes we rely on a Fuzzy Regression Discontinuity Design where the probability to be assigned to the treatment, i.e. the number of hours of remedial courses effectively attended by each student, is a discontinuous function of the placement test score. In particular, we estimate the following model by using a Local Linear Regression (LLR) approach in the neighbourhood of the MSE-optimal bandwidth (Calonico *et al.*, 2018):

$$Y_i = \beta_0 + \beta_1 Hours\_of\_Remedial\_Courses_i + \beta_2 g(test\_score_i) + \beta_3 X_i + \mu_k + \varepsilon_i \tag{1}$$

$$Hours\_of\_Remedial\_Courses_i = \gamma_0 + \gamma_1 Assigned\_Treatment_i + \gamma_2 s(test\_score_i) + \gamma_3 X_i + \mu_k + v_i \tag{2}$$

In equation (1) Y_i is the outcome variable of student *i.* $Hours\_of\_Remedial\_Courses_i$ defines the number of effective hours spent by student i attending the remedial courses, whereas $g(test\_score_i)$ and $s(test\_score_i)$ are first-order polynomials of the normalised forcing variable (the raw test score minus the threshold level decided by each Degree Course). We further control for a first-order interaction term between

[1] AlmaLaurea is an Italian interuniversity consortium that surveys each year about 90% of graduates.

the treatment and the normalised forcing variable. X_i includes a set of students' characteristics, i.e. age, gender, high-school grade and lyceum dummy, μ_k are field of study dummies, whereas ε_i and v_i are the error terms.

In equation (2), referring to the First-stage, the variable $Hours\_of\_Remedial\_Courses_i$ is instrumented with $Assigned\_Treatment_i$ that is a dummy taking the value 1 if a student is assigned to the remedial program ($test\_score_i \leq 0$) and 0 otherwise.

It should be stressed that the placement test score could not be easily manipulated for different reasons: students were not allowed to resit the placement test; the remedial allocation rule was not announced before taking the test, and scripts were marked by external examiners.

In Figure 1 we check the continuity of the forcing variable implementing the procedure developed by Cattaneo *et al.* (2020): the estimated difference in the density of $test\_score_i$ at the cut-off is -0.16, and it is not significant at any conventional level (*p-value*: 0.87). In Figure 2 we also present some descriptive graphs of the predetermined covariates plotted against the forcing variable nearby the cut-off: no jumps at the threshold are detected.

4. Results

Results are reported in Table 1, where in each specification standard errors are robust to heteroskedasticity and clustered at the test score level.

The First-stage (Panel B) shows that the assigned treatment strongly correlates with the effective treatment: around the threshold, being assigned to the treatment leads to about 21–59 more hours of remedial courses. Figure 3 depicts a large discontinuity in the probability of attending remedial lectures: for those who scored below the threshold this probability is 0.51, while it drops to just 0.01 for students who obtained a score above the cut-off.

In Panel A, TSLS estimates show that the attendance of 50 hours of remedial courses increases the probability of getting the degree by about 12 percentage points (column 1), and this effect is significant at the 5 percent level. Similar results are found when we measure the academic performance as the probability to graduate on time (column 2) or the probability to obtain the degree within one additional year (column 3). No effect is found on the graduation mark (column 4), while we show that having attended 50 hours of remedial lectures reduces by about 1 year the delay students face in obtaining a degree (column 5). Instead, remediation does not affect any labour market outcomes built using both data from AlmaLaurea (column 6) and phone interviews (column 7-9).

Finally, we show the intention-to-treat (ITT) effects in Panel C of Table 1 relying on a Sharp RDD estimated through a local linear regression within the MSE-bandwidth. Being assigned to the treatment significantly affects the same outcomes as displayed in Panel A in which the LATE are reported.

In Figure 4 and 5 we show the average value of educational and labour market variables, respectively, as a function of the normalised test score. The fitted plots that are linear best fits, performed separately on either side of the cut-off, and the confidence intervals at the 95 percent level are also reported. Overall, the descriptive graphs confirm the results displayed in Table 1 (Panel C).

5. Conclusion

We find a positive long-run impact of remedial courses on academic outcomes, suggesting that remediation can be a valid policy tool for students to conclude their studies, to graduate on time and, in the case of delay, to graduate within a reasonable timeframe. Nevertheless, remediation is proved to be ineffective in providing students with relevant skills to find a job as we find no indication that remediated students have better labour market outcomes than comparable non-remediated counterparties.

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Appendix

Figure 1. Manipulation of the forcing variable

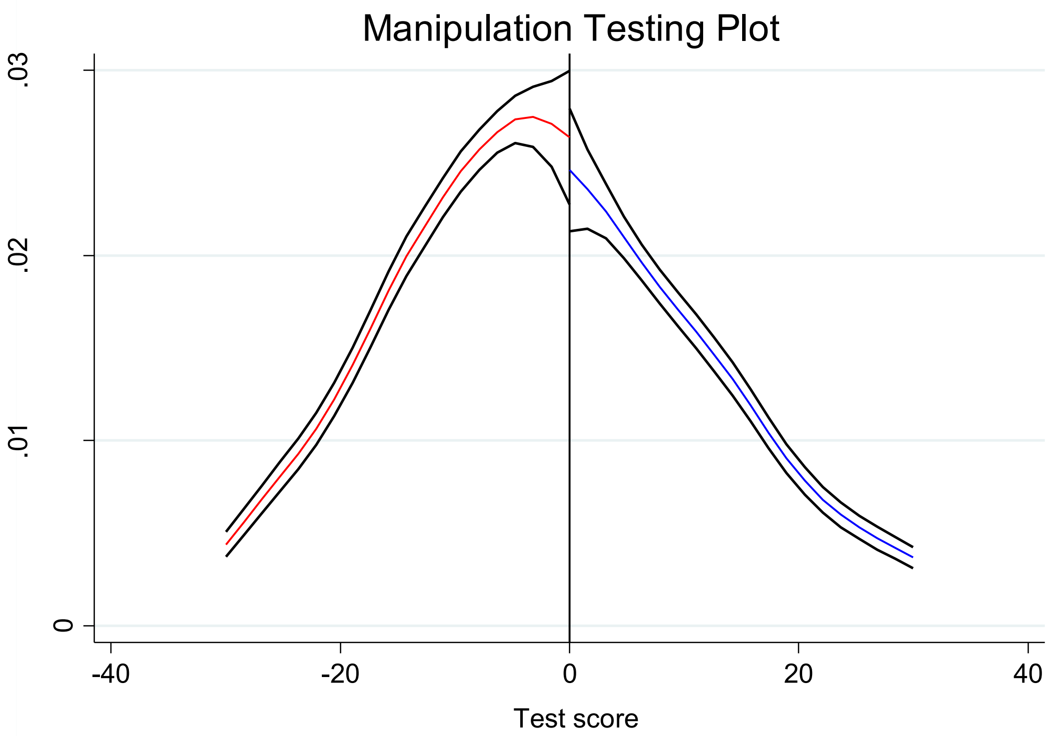
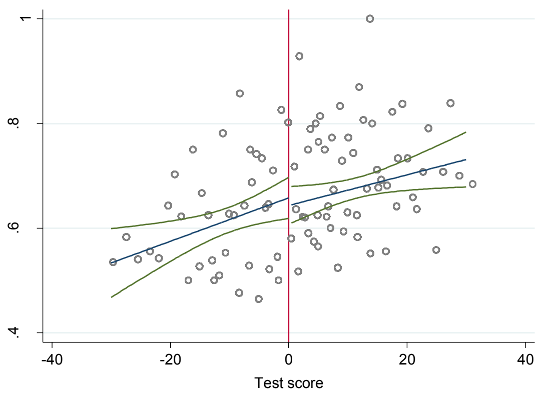
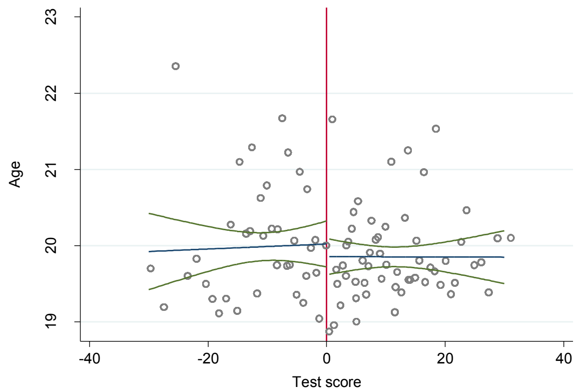
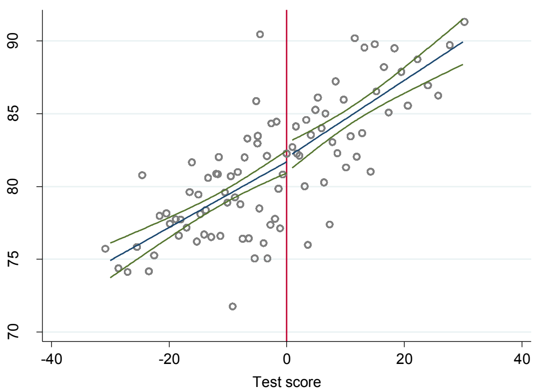


Figure 2. Discontinuity in the covariates







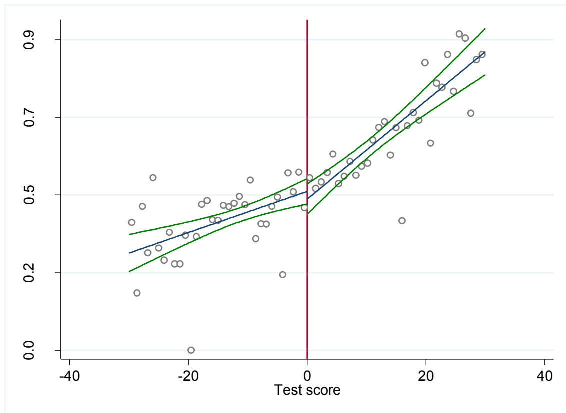


Figure 3. Discontinuity in the probability to participate into the remedial program

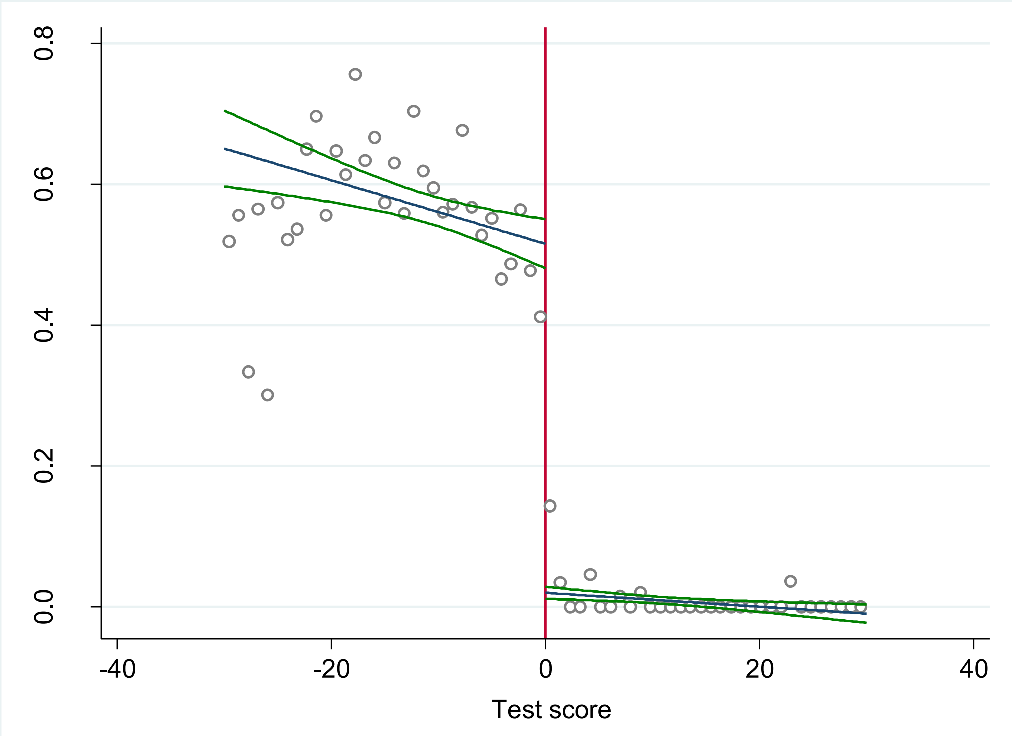
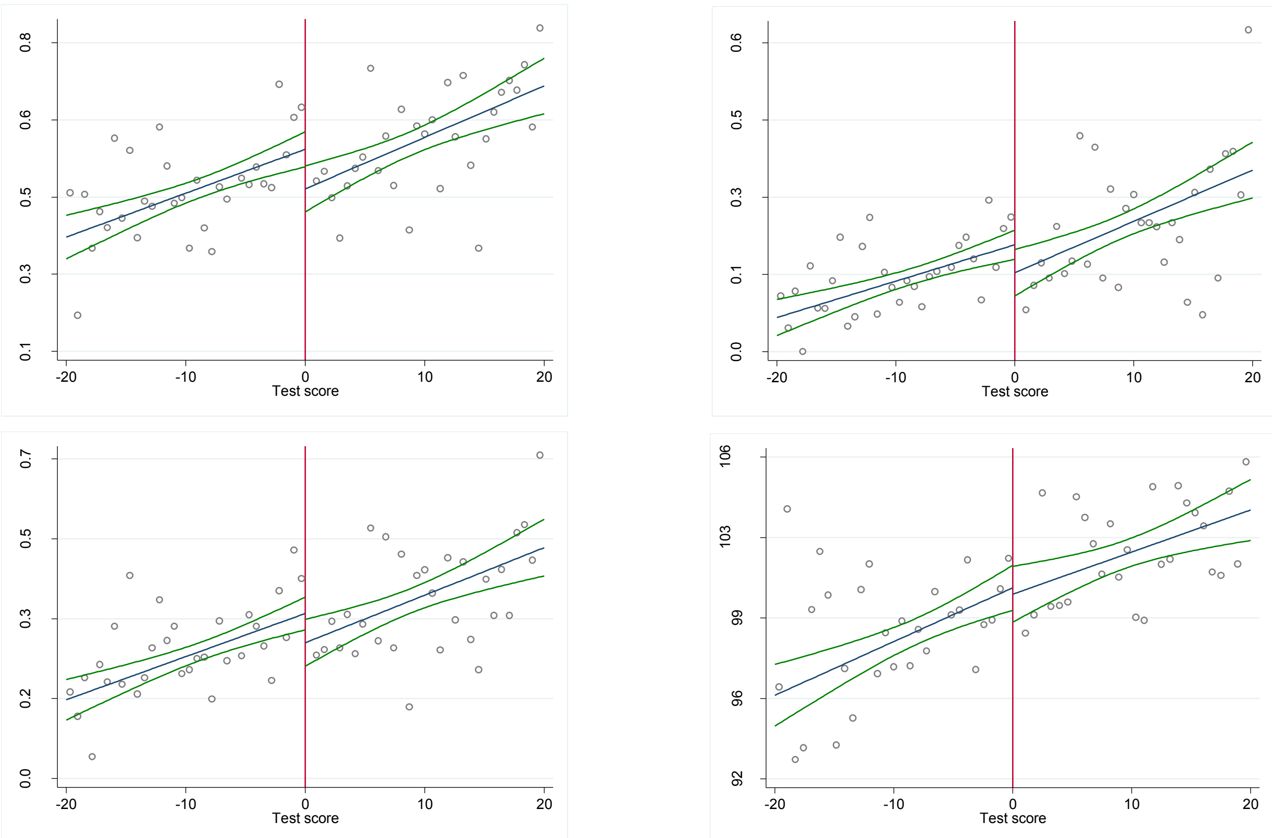


Figure 4. Discontinuity in the educational outcomes



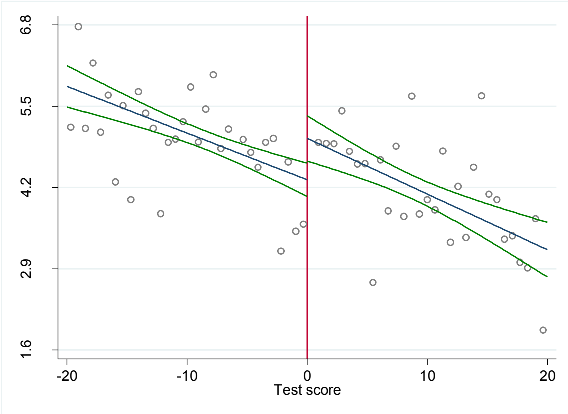


Figure 5. Discontinuity in the labour market outcomes

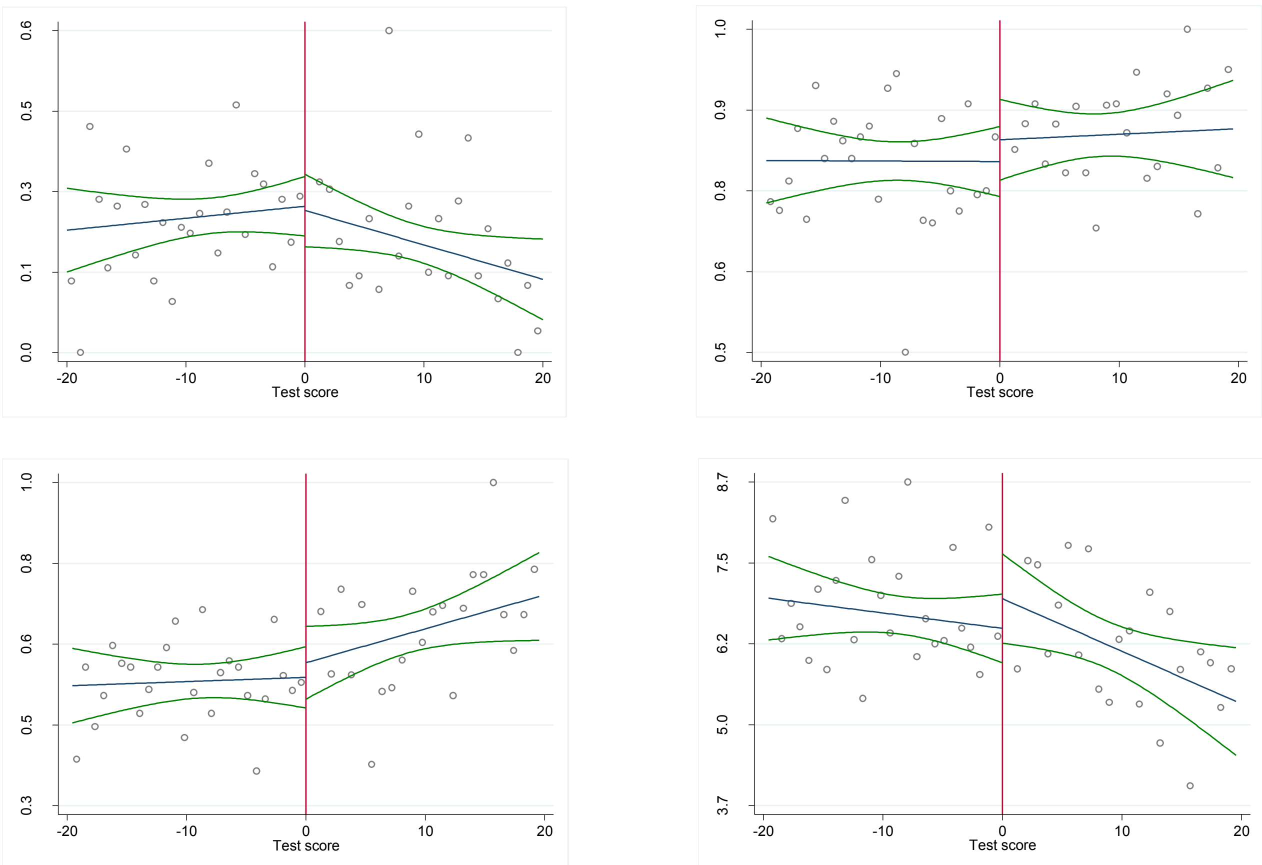


Table 1. Effect of remedial courses on educational and labour market outcomes – Fuzzy and Sharp RDD estimates – LLR with MSE-bandwidth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Graduation	Graduation on time	Graduation within one year	Graduation mark	Graduation delay	Employed after one year	Employed in the past	Currently employed	Years to find a job
					Panel A: TSLS estimates				
Hours of Remedial Courses	0.0024**	0.0018*	0.0017*	0.0278	-0.0217**	-0.0012	-0.0004	0.0017	-0.0064
	(0.0012)	(0.0010)	(0.0009)	(0.0241)	(0.0083)	(0.0015)	(0.0021)	(0.0032)	(0.0146)
					Panel B: First-stage				
Assigned Treatment	53.8359***	49.5013***	55.8185***	54.4819***	53.5571***	58.6111***	36.3659***	20.7709***	36.3985***
	(5.2060)	(5.6676)	(4.7906)	(6.5132)	(5.2336)	(7.4767)	(9.7377)	(8.8051)	(9.7637)
					Panel C: Intention-to-Treat				
Assigned Treatment	0.1544**	0.0793*	0.0988*	1.0749	-1.2138***	-0.0359	-0.0444	-0.0011	-0.1785
	(0.0619)	(0.0423)	(0.0504)	(1.1286)	(0.3902)	(0.0862)	(0.0753)	(0.0755)	(0.5218)
Forcing Variable Polynomial	First	First	First	First	First	First	First	First	First
Interaction Term	First	First	First	First	First	First	First	First	First
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field of Study FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,512	1,194	1,721	895	1,443	681	422	296	423

Note: The outcome variable is reported on top of each column. Each specification includes controls in vector *X* and field of study fixed effects. Standard Errors are robust to heteroskedasticity and clustered at the test score level (reported inside the brackets). Significance at the 10% level is represented by *, at the 5% level by **, and at 1% level by ***.