The Effectiveness of Remedial Courses:
An Analysis on Freshmen in Industrial Engineering

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Abstract
Under-preparation is one of the main driving forces behind poor academic performance by under-graduate students. Higher education institutions often launch remedial courses as an inclusive solution to help academically deprived freshmen fill their knowledge gaps. However, the substantial resources absorbed by remedial courses raise recurrent concerns about their suitability. This paper exploits 2012-2016 administrative data from a medium-size university in Northern Italy to appraise the effectiveness of the remedial courses undertaken by newly enrolled students in industrial engineering who fail to achieve the university entry test cut-off score.
The outcomes of the empirical analysis provide an articulated picture. The two-year drop-out rate of students who successfully complete a remedial course is not statistically different from that of nonremedial students, whereas significant differences exist in the number of earned credits. However, in two years also this difference disappears when the control group restricts to students who could enrol in an undergraduate course without need for remedial education thanks to a performance just above the cut-off score.

Keywords
Remedial courses; higher education; undergraduates; knowledge gap; industrial engineering

1. Introduction

In 1998 23.8% of younger adults aged between 25 and 34 in OECD countries had a tertiary education degree. Twenty years later, in 2017, the same figure had ramped up to 44.5% (OECD, 2018). This spectacular growth was stimulated by the constantly increasing sophistication of technologies and organisations and by a parallel growth in the return to the educational qualifications required to govern complexity in different knowledge domains, which boosted both demand and supply of higher education.

The rapid expansion of numbers in tertiary education in recent years has seen the raise of new problems, without necessarily solving the older ones. The overall increase of college and university graduates did not always alleviate horizontal mismatch between demand and supply. Concerns have been periodically raised about a decline in the number of college graduates in the so-called STEM fields[1], particularly in engineering (Kreysa, 2006; Ehrenberg, 2010; Faulkner *et al.*, 2014).

In addition, the massification of higher education brought in larger diversity among higher education institutions (Rossi, 2010; Faulkner *et al.*, 2014) and a more pronounced heterogeneity in students' skills, prior knowledge, and interests (Derr *et al.*, 2018). Higher dispersion in the quality of both students and universities entails at least two noteworthy consequences. First, universities face a constant trade-off between the need for more standardised processes, to provide objective information to students and prospective employers, and the demand for tailored solutions, to suit the needs of diversified students. Second, the higher variance in the human capital of graduates lowers the signalling value of academic certificates and raises information asymmetries and coordination costs both between students and universities and between graduates and employers. Moreover, radical reforms of the tertiary education systems aimed at accommodating the ongoing structural changes, such as the Bologna process in EU countries, initially intensified confusion among stakeholders by questioning long-established reference models in higher education.

On top of the above, in many OECD countries the demand for college skills has fallen behind the growth in the supply of graduates and post-graduates from tertiary education (Okay-Somerville and Scholarios, 2013). Coupled with greater variance in the human capital of younger graduates, excess supply generated an increasing competition for the best jobs and the segregation of less competent (or less competitive) graduates to unattractive or non-graduate jobs. The economic crisis after 2008 further aggravated this competition, thanks also to a generalised weakening of employment protection legislation.

[1] STEM is the acronym for Science, Technology, Engineering and Mathematics.

The massification of tertiary education, in summary, challenges universities to educate growing numbers of increasingly differentiated students in diversified fields and prepare them for uncertain and lengthy professional careers, still accounting for limited resources. Overall, existing indicators suggest large room for improving the return to private and public investment in higher education. For instance, drop-out rates are a prominent source of concern, especially in the case of STEM students (Ehrenberg, 2010; Kokkelenberg and Sinha, 2010). Based on an international comparison across 20 OECD countries McGrath *et al.* (2014) report an average 37.1% graduation rate among students enrolled in higher education, which lowers to 36% in European countries and to 32% in Italy, the country of the case study presented in this paper.

A solution to improve students' success rate is recognised in measures able to reduce diversity among candidates to tertiary education, for instance by mitigating students' gaps in prior knowledge. Higher education institutions actively participate in controlling freshmen's heterogeneity by increasing involvement in setting of selection criteria, selection processes, and application management (McGrath *et al.*, 2014). In Italy the Ministerial Decree 270/2004 transfers to the learning regulations of universities the definition of the minimum requirements for enrolment, the identification of assessment tools and the assignment of additional credits beyond curricular standard called OFA (*Obblighi Formativi Aggiuntivi* – Additional Educational Requirements) in case of missing basic requirements.

Among the tools aimed at equalising initial knowledge levels a prominent role is played by remedial courses[2], also labelled as learning assistance or developmental programs (Kreysa, 2006), which aim at providing under-prepared new entrants with the knowledge and competences they need to appreciate first-year academic courses, especially in the case of undergraduate studies. Participation in remedial courses, voluntary or mandatory, is usually elicited by tutors and counsellors, or by the outcomes of an admission test. Remedial courses often include a final test to help participants assess their progresses and their additional learning needs. The literature reports contrasting evidence of the impact of remedial courses on outcome variables such as student persistence, attainment of higher education certificates, credits earned, or success in first-year key-exams (Kreysa, 2006; Bahr, 2008; De Paola and Scoppa, 2014; Duchini, 2017; Boatman and Long, 2018; Derr *et al.*, 2018). These contrasting outcomes, which may be explained by considerable differences in the contents, the target audience, and the governing rules of the examined support initiatives, call for additional research.

[2] Other tools include student orientation and admission tests.

The empirical analysis developed in this paper provides further evidence on the effectiveness of remedial courses for students who recover successfully from initial gaps in mathematics by focusing on a medium-size university in Northern Italy where newly enrolled students in engineering who fail to achieve a cut-off score at the admission test are assigned to an intensive remedial course in mathematics. At the end of the remedial course freshmen who pass a final exam (offered five times during the academic year) can register for the regular exams of their undergraduate programme and earn academic credits, whereas non-passing students are forced either to retake the admission test the following academic year or to drop out. Observed data concern five cohorts of students who enrolled in three undergraduate programmes in industrial engineering between 2012 and 2016.

Assignment to a remedial course is modelled as a treatment impacting outcome measures that describe academic success, whereas students who pass the admission test provide a suitable control group. The impact of the exposure to treatment is further decomposed to outline differences between the outcome of students who comply with the assigned treatment and pass the remedial exam and the outcome of noncompliers, who fail the post-remedial exam. To account for the non-random distribution of pre-treatment individual characteristics that affect the probability of selection into the treatment group the empirical analysis takes advantage of a doubly robust estimation method that combines a regression model with propensity score matching (Wooldridge, 2010; Funk *et al.*, 2011).

The outcomes of the empirical analysis provide an articulated picture. The two-year drop-out rate of students who successfully complete a remedial course is not statistically different from that of nonremedial students, whereas significant differences exist in the number of earned credits. However, in two years also this difference disappears when the control group restricts to students who could enrol in an undergraduate course without need for remedial education thanks to a performance just above the cut-off score.

The rest of the paper is organised as follows. The next section discusses the literature on the effectiveness of remedial courses in tertiary education and outlines the research hypothesis. Section 3 provides information on the remedial course policy adopted by the examined university and characterises the population of freshmen who enrolled in undergraduate courses in industrial engineering between 2012 and 2016. Section 3 also details the empirical strategy to assess the effectiveness of remedial courses, whose results are presented in section 4. The final section discusses the paper outcomes and outlines some concluding remarks.

2. Background and research hypothesis

The antecedents to student success in higher education have long been researched in the literature (Perlberg, 1967; Bahr, 2008). However, if early motivations mainly rooted in the search for screening tools to grant access to the most promising candidates, the massification of tertiary education surely contributed to re-focus the analysis on preadmission indicators of poor academic performance able to identify under-prepared students in need of additional support.

Significant predictors of academic performance typically correlate with field-specific prior knowledge, with the regularity of the schooling career, and with the socio-economic background of candidates (Perlberg, 1967; Hagedorn *et al.*, 1999; Kreysa, 2006; Ehrenberg, 2010; Kokkelenberg and Sinha, 2010; Rask, 2010; Faulkner *et al.*, 2014; Cerdeira *et al.*, 2018; Derr *et al.*, 2018; Windle *et al.*, 2018). Prior knowledge is usually measured by high school outcomes (grade point average, GPA, or score achieved at high school final exam), by the coherence between high school type and tertiary education field of studies, and by performance in the admission test[3]. The regularity of the schooling career, usually significantly correlated with academic success, accounts for delays in the achievement of the secondary school certificate and for possible gap years between the end of the secondary school and the beginning of tertiary education. Eventually, the socio-economic background is measured by a range of factors that generally include candidates' gender, nationality, and area of residence, as well as indicators of family support such as parents' education or occupation[4].

The literature has underlined important peculiarities of the predictors of academic success in engineering studies compared to other disciplinary fields. The academic outcomes of freshmen in engineering display a higher elasticity to the scores obtained in the mathematics section of admission tests (Kokkelenberg and Sinha, 2010). In addition, domain-related prior knowledge developed at secondary school plays a more crucial role (Derr *et al.*, 2018), possibly due to the cumulativeness that characterises mathematical knowledge across the subsequent courses of engineering undergraduate programmes (Rask, 2010; Derr *et al.*, 2018).

The stronger importance of field-specific and especially mathematical prior knowledge for freshmen in engineering stresses the importance of remedial courses as a

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[3] The predictive power of different indicators of prior knowledge depends on the considered output measure. For instance, Grilli *et al.* (2016) show that performance in the reading section of the admission test impacts early outcomes, whereas a low score in the area of mathematics correlates with a slow progression in studies. Söderlind and Geschwind (2017) compare the predictive power of an aptitude test with high school GPA and find that the former predicts retention rate, whereas GPA predicts credits earning.

[4] Cerdeira *et al.* (2018) find that the predictive power of parents' education is negligible after controlling for past success measures such as secondary school GPA or access exam scores.

solution to synchronize candidates' initial competences and improve overall success rates. At the same time, the cumulative nature of the involved knowledge questions the possibility to solve deep-rooted gaps by means of a short-term treatment such as a remedial course, thus justifying the search for additional empirical evidence.

Remedial courses are a long-established tradition in the US (Kreysa, 2006), especially in the case of community colleges[5] (Bahr, 2008). In contrast, remedial courses are much less frequent in Europe, where their diffusion has been driven in more recent years by increasing participation rates in higher education (Faulkner *et al.*, 2014).

Remedial courses bring together a wide range of initiatives that, besides sharing the common target of providing under-prepared students with the floor requirements to appreciate college-level education, can be highly differentiated. Consequently, the variety of judgements resulting from their appraisal comes as no surprise. Kreysa (2006) and Bahr (2008) assess the impact of semestrial remedial courses provided by US higher education institutions. Despite significant differences in the examined cases (Kreysa focuses on a cohort of students enrolled in a large private university, whereas Bahr considers freshmen from several cohorts in Californian community colleges) both studies conclude that remedial courses enable participants to catch up with better prepared students and outline non-significant differences in drop-out rates and graduation rates. Nevertheless, it has to be underlined that the econometric models estimated by Kreysa (2006) and Bahr (2008) account for the average impact of control variables that affect academic performance, but do not explicitly address the higher concentration of "risk factors" among under-prepared students. In addition, besides outlining the positive outcomes of students who successfully complete a remedial course, Bahr (2008) also underlines that the large majority of remedial students eventually drop out from tertiary education without completing the remedial path.

Derr *et al.* (2018) and De Paola and Scoppa (2014) focus on a German and an Italian case, respectively, where participation in the remedial course is not mandatory, but is chosen by students based on the outcome of an entry test. Remedial courses thus include also students whose performance fell above the cut-off score. De Paola and Scoppa (2014) examine a two-month remedial course involving 160 hours of face-to-face teaching in either mathematics or English, whereas Derr *et al.* (2018) describe a mixed solution involving different combinations of self-learning based on on-line resources, e-tutoring, and a one-week on-campus workshop aimed at improving mathematical

[5] According to Kreysa (2006) remedial courses are offered by 76% of higher education institutions in the US, whereas Bahr (2008) reports that a share between 28% and 41% of US students in higher education participate in remedial courses.

skills[6]. Both cases report a positive causal effect of participation in a remedial course on academic performance. However, Derr *et al.* (2018) do not provide separate results for students who either passed or failed the entry test, besides overlooking the different distribution of the predictors of academic outcomes between participants and non-participants in remedial courses. De Paola and Scoppa (2014) adopt a more sophisticated approach and apply a fuzzy regression discontinuity design that rules out the risk of comparing populations with different pre-treatment characteristics by focusing on students who performed just above or just below the cut-off point in the university admission test. Accounting also for the intensity of participation in remedial courses those authors show that learning assistance lowers drop-out rates and increases the number of credits earned in the first academic year compared to the control group. Still, regression discontinuity design does not allow to assess the impact of remedial courses for the students who classify in the lowest tail of score distribution at the admission test, who are discarded from the empirical analysis. This limit is inherent also to the empirical strategy adopted by Duchini (2017), who implements a sharp regression discontinuity design to estimate the impact of the maths remedial course administered to the freshmen of the economics department of an Italian university who fail the admission test. The examined situation prospects stricter rules of exit from the treatment compared to the above cases. At the end of the remedial course students undergo a formal assessment (under the form of a university exam) whose failure conditions the academic path by blocking registration for key first-year exams. The remedial course consists of 21 hours of face-to-face teaching and the authoress ascribes to its brevity the lack of a significant impact on participants' academic outcomes. Boatman and Long (2018) also make use of regression discontinuity design to calculate the causal effects of remedial courses in Tennessee universities and identify null or even negative impact in the case of students with an entry test performance just below the cut-off point. However, they also identify significant positive effects for students who failed the admission test by large margins. These outcomes stress the importance of not limiting the analysis to students whose performance in the entry test falls near the cut-off point, because the impact of remedial courses could vary depending on the degree of initial (under)preparation.

The brief survey of the literature provided above has outlined the great variety in the remedial courses offered to new entrants in tertiary education. Remedial courses may differ in assignment rules, contents, structure, intensity, and exit rules. In addition, the

[6] In addition, both cases provide information on the frequency of participation in the remedial initiatives, gathered from either access to on-line resources (Derr *et al.*, 2018) or records of presence in lectures (De Paola and Scoppa, 2014).

empirical strategies adopted by researchers vary in the solutions adopted to account for heterogeneity in the distribution of pre-treatment variables affecting academic outcomes between remedial and non-remedial students and in the choice of the observations to be included in the empirical analysis. Consequently, definitive evidence of the effectiveness of remedial courses is still lacking. This is particularly true in the European context, where extensive resort to developmental programs within tertiary education is comparatively recent and implemented actions are usually "lighter" when compared to the corresponding semester-long courses in the US.

The analysis developed in the next sections contributes to the debate on the most suitable tools to improve students' academic performance by providing additional evidence on the effectiveness of the remedial courses in mathematics provided to under-prepared new entrants in engineering undergraduate programmes by an Italian university. The adopted empirical strategy accounts for the non-random distribution of pre-treatment variables that affect outcomes and the probability of assignment to a remedial course among newly enrolled students, for heterogeneous knowledge levels among remedial students, and for noncompliance with the assigned treatment. In particular, the empirical analysis tests the following research hypothesis.

> *Remedial courses are effective tools to help under-prepared new entrants in tertiary education to catch up with the academic outcomes of adequately prepared students.*

3. Data and empirical strategy

3.1. The dataset

This study is based on administrative data on 2,341 unique individuals from five cohorts (2012-2016) of first-time, true freshmen (never previously enrolled in higher education) entering three under-graduate programmes in industrial engineering (automation engineering, management engineering, and mechanical engineering) run by the mechanical engineering department of a medium-size university in Northern Italy[7]. The observed undergraduate programmes conform to the European Credit Transfer and Accumulation System (ECTS), which measures exam workload in terms of credits (one academic credit corresponds to 25 hours of study) and sets a standard of about 60 credits to be earned in one academic year. Graduates in engineering are in high demand

[7] The complete dataset includes observations on 84 additional new entrants, who were excluded from the analysis because 82 transferred from other universities, whereas two deceased after enrolment. In addition to the above limitations, eight students for whom administrative data report more than 69 credits earned in the first academic year and 20 students with more than 69 credits in the second academic year, compared to 60 credits per year of standard curricula, were excluded from the empirical analysis.

in the local labour market, due to a strong presence of manufacturing and service employers. The periodical survey of young graduates from higher education in Italy by Almalaurea (2019) confirms the match between labour demand and supply, with employment rates of 95.3% and 97.7%, respectively, among graduates and postgraduates in industrial engineering active in the labour market one year after graduation.

A preliminary assessment of the obstacles to a successful academic path is provided in Table 1, which compares the recent performance in a set of three indicators by students in the observed undergraduate programmes at the examined university and at all remaining Italian universities. The data show that the observed students experience a more difficult start compared to their national counterparts. However, candidates who overcome the initial obstacles manage to outperform the national average when it comes to graduation time. Figures in Table 1 therefore confirm the importance of concentrating support actions at the beginning of the academic experience. Coherently, over the last years the academic staff of the engineering faculty at the examined university has devoted significant efforts to design, experiment, and adapt admission tests and remedial courses.

In line with other European countries (see, *e.g.*, Derr *et al.*, 2018), nearly all engineering faculties in Italy administer admission tests on STEM subjects and provide pre-courses and remedial courses in mathematics to under-prepared freshmen. Admission tests usually take place in the spring of the last year of secondary school[8], with a final call in early September. Candidates who do not achieve a minimum score are assigned additional credits beyond curricular standard (the already mentioned OFA), which will be earned by passing an exam supported by a remedial course. After earning the additional credits, the initially under-prepared students can register for regular curricular exams, otherwise unavailable. Nevertheless, in most cases remedial courses have limited duration. Moreover, in the attempt to save resources, on-line courses are increasingly preferred over face-to-face ones. In contrast with the prevailing trends, the faculty staff at the sampled university chose to invest in a 36-hour course of face-to-face lectures accompanied by on-line resources to guide self-study. Remedial courses take place in the first semester during dedicated time slots that do not overlap with other freshmen lectures in the same semester. The important human, financial, and organisational resources involved thus make the investigation of how those support courses impact the performance of remedial students particularly important.

[8] As a means of attracting high-profile candidate and orienting the end of secondary education studies to the chosen academic field a growing number of Italian universities encourage prospective students to take the admission test one full year before enrolment.

Figure 1 depicts admission test performance by students who enrolled in the examined engineering programmes between 2012[9] and 2016. It has to be noted that 3.7% of freshmen, corresponding to 86 individuals, did not take the initial test, due to late enrolment after the last call for the admission tests. These students are assigned OFA by default and are supposed to participate in remedial courses. However, since assignment to treatment does not depend on the assessment of gaps in prior knowledge deemed important for the chosen curriculum those students were excluded from the empirical estimates. A notable 23.7% fails to pass the admission test, which requires a minimum score of 15/40[10]. The majority of remedial students (386 over 554) succeed in passing the exam to earn the OFA credits, whereas the remaining 168 do not comply with this requirement and are consequently forced either to re-enrol as freshmen the following academic year (and retake the admission test) or to drop out. Figure 1 points out that test scores are significantly dispersed also among non-remedial students. Good starters, which include 44.4% of enrolled students, identify candidates who passed the admission test with a score above 120% of the cut-off point (*i.e.*, above 18/40), whereas a substantial 28.3% of freshmen (named as Poor starters) overcame the floor requirement of the admission test by less than 20%.

[Table 1 about here]

[Figure 1 about here]

3.2. Empirical strategy

The empirical analysis aims at assessing the existence of a statistically significant impact of remedial courses on the performance of under-prepared new entrants. This is equivalent to estimate how assignment to and receipt of a treatment (*i.e.*, a remedial course) impact the academic performance of remedial students compared to the control group of students who scored above the cut-off point in the university entry test.

A direct comparison between the performance of treated and untreated individuals provides an unbiased estimate of the causal effect of the treatment only in randomised experiments, *i.e.*, when the covariates that may affect both selection into treatment and observed outcomes are equally distributed across the two groups (Wooldridge, 2010;

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[9] Observations begin in 2012 because prior to this year students' career registrations did not record the earning of OFA credits, which have no impact on official GPA and curricular credits count.

[10] Administered test are designed and evaluated by an inter-university consortium (*Consorzio Interuniversitario Sistemi Integrati per l'Accesso*, CISIA) that groups 48 Italian universities. In the examined years the admission test included 5 questions on logics, 20 questions on mathematics, 10 questions on natural sciences, and 5 questions on verbal comprehension. Right answers increase score by 1 point, missed answers involve no penalisation, and wrong answers involve a penalty of 0.25 points.

Funk *et al.*, 2011). Outcome regression on treatment conditional on relevant confounders offers a basic solution to account for non-random differences between the treated and the control group. Regression adjustment offers a more sophisticated approach by calculating counterfactual outcomes adjusted for the covariates. The covariate coefficients estimated based on the sample of treated (untreated) individuals are used to calculate the predicted outcome under treatment (non-treatment) for control (treated) individuals. The outcome observed for each individual is thus complemented by a counterfactual prediction of the potential performance that may have been observed in a different situation, *i.e.*, under no treatment in the case of treated individuals and under treatment for the members of the control group. The average causal effect of treatment in the observed sample (the so-called average treatment effect, ATE) is therefore calculated as the mean difference between observed and predicted outcomes for the treated, minus the mean difference between observed and predicted outcomes for controls. Alternatively, the ATE can be defined based on the concept of mean potential outcome (mean PO) under (no) treatment, which is the mean performance that would be observed if all sampled individuals would (not) undergo treatment, and is calculated as the mean of individual observed or counterfactual outcomes corresponding to the situation of (no) treatment. The ATE is thus the difference between the mean PO under treatment and the mean PO under no treatment. An additional parameter of interest is the average treatment effect on the treated (ATET), which corresponds to the mean causal effect of the treatment for the individuals who actually received the treatment and is calculated as the difference between the mean PO under treatment and the counterfactual mean PO under no treatment, both calculated for the sole members of the treatment group.

Regression adjustment provides unbiased estimates of treatment effects as far as the underlying model is correctly specified and includes all the covariates that may affect the relationship between assignment to the treatment and the observed outcome. A different estimation strategy to account for non-random distribution of risk factors in treatment and control groups is based on weighting observations according to the probability of selection into treatment. In particular, inverse probability weighting exploits the possibility of recovering the population mean of an outcome variable by weighting observations by the inverse of the probability of selection (Wooldridge, 2010, p.823). Accordingly, inverse probability weighting models calculate the probability of selection into treatment conditional on pre-treatment covariates (the so-called propensity score) and re-weight observations to obtain a randomised subpopulation before comparing the outcomes of treated and untreated individuals. However, also in this case model misspecification could undermine the acceptability of the estimated parameters.

By combining regression adjustment and propensity score weighting doubly robust estimators provide a convenient solution to test the causal effect of selection into a treatment on an outcome variable of interest and simultaneously reduce the risk of model misspecification (Funk *et al.*, 2011). Doubly robust estimators require to model individual propensity to treatment as a function of pre-treatment covariates, usually in the form of a binary regression model, and to specify a regression model for the outcome variable, which is used to calculate individual predicted outcome. The inverse weights applied to the observed outcomes and the counterfactual outcomes predicted for treated and untreated individuals are based on propensity scores. Doubly robust estimators offer robustness to misspecification of the parametric models because they require only the regression adjustment model or the propensity score model to be correctly specified to provide unbiased outcomes (Wooldridge, 2010, ch.21). Within the family of doubly robust estimators, inverse-probability weighted regression adjustment (IPWRA) estimators weight observations by the inverse probabilities of treatment to correct the regression adjusted model in case of misspecification of the latter (StataCorp, 2017).

The parameter that best apprises the impact of assignment to treatment on the academic outcome of students who perform below the cut-off point in the university admission test is the ATET, which quantifies the differential outcome of remedial students compared to the mean potential outcome that would be observed in case of no treatment. However, in the examined testbed a mandatory exam at the end of the remedial course conditions the further developments of the academic career and not all remedial students manage to pass it. Consequently, the ATET coefficients average the performance of two markedly different sub-groups. On the one hand, remedial compliers take the remedial course, pass the OFA exam, and start to register for curricular exams. On the other one, remedial non-compliers do not register for or fail the OFA exam and drop-out or idle at university. Accordingly, ATET is the weighted mean of a complier average causal effect (CACE) and a noncomplier average causal effect (NACE):

$$\text{ATET}=p*\text{CACE}+(1-p)*\text{NACE} \qquad (1)$$

where p is the proportion of compliers among students exposed to the treatment.

When the performance level of noncompliers can be identified, the CACE can be estimated after calculating the ATET coefficient to appraise the specific impact of treatment on more engaged students. Thus, the hypotheses about the NACE strongly condition the identification of the researched CACE. In case of free exit from a remedial course, assignment to the treatment is exogenous to the outcome variable and can be used to instrument actual participation in the remedial course. Under the hypothesis of independence between treatment assignment and outcome (the so-called exclusion restriction) noncompliers are assumed to achieve the same performance they would display under no treatment, with a consequent null value of the differential NACE effect (Imbens and Rubin, 2015, ch.23). However, in case of a binding final exam assignment to the treatment conditions both treatment receipt and expected performance, thus violating the exclusion restriction. Bahr (2008) indicates a solution to this identification problem by switching the attention from compliance and noncompliance with treatment receipt to compliance and noncompliance with the exit rule, yet at the price of measuring the effectiveness of completing a remedial course instead of the effectiveness of the remedial course itself[11]. This paper adopts a similar approach considering that the exit rule constraints the outcomes of noncompliers and sets the differential NACE effect to values that counterbalance the potential outcome of those students.

3.3. Outcome variables and independent variables

This section provides information on the outcome variables and the covariates used in the empirical analysis. Table 2 reports the correlation indexes between five dimensions of performance measured at different steps of the academic career. When calculated, the high values and the high significance of correlations in Table 2 suggest that a good start has a high chance to turn into a long-term success. Accordingly, the outcome variables to assess the effectiveness of remedial courses may focus on the early years of university without the risk of neglecting outcome patterns that could arise later on. Since long-term measures exclude observations from the most recent cohorts, for which late-career information is not yet available, this approach has the additional benefit of increasing the number of available observations. Therefore the empirical analysis focuses on outcome variables that measure students' performance one or two years after enrolment, namely the number of curricular credits earned in the first academic year (variable Credits1), the number of curricular credits earned in the first and second academic years (variable Credits2), and drop-out from the initial curriculum by the end of the second academic year (variable DropOut2).

Table 3 reports some descriptive statistics of the chosen outcome variables by performance in the admission test and in the subsequent remedial action. Not surprisingly, among test takers the average performance steadily improves from

[11] Duchini (2017) also focuses on the effectiveness of successfully completing a remedial course but does not explicitly disentangle the outcomes of remedial students who pass the exam to exit the remedial status from those of non-passers.

remedial students who do not comply with the mandatory OFA exam[12] to nonremedial Good starters. However, the large standard deviations that accompany the average measures suggest high heterogeneity also among students within the same group. Students who enrol without taking the admission test display the highest standard deviations relative to mean values and the highest propensity to drop out from the initial academic path. This evidence corroborates the intuition that the group of test no-takers includes highly heterogeneous individuals whose characteristics do not overlap with remedial students and should accordingly be excluded from the empirical tests.

[Table 2 about here]

[Table 3 about here]

The independent variables of the outcome regression model and the drivers of propensity to select into treatment were identified based on the literature survey in section 2. Table 4 reports some basic statistics for the chosen covariates and specifies their use in the empirical estimates. Variables that reflect students' prior knowledge include the grade achieved at the high school final exam and the fields of study privileged in secondary education (quite predictably, most freshmen in engineering attended science-oriented or technical-oriented high schools), which also reveal students' cognitive interests.

[Table 4 about here]

Personal attitudes and interests also reflect in the choice of a specific undergraduate programme because, despite common membership in the area of industrial engineering, courses in automation engineering, mechanical engineering, and management engineering focus on specific application fields and prospect significantly differentiated professional careers. It has to be noted that these variables cannot be included among the drivers of selection into treatment, because participation in the admission test that determines the assignment to a remedial course (*i.e.*, assignment to a treatment) precedes the choice of the undergraduate programme.

Departure from a standard education career revealed by late age of entry may provide another signal of gaps in prior learning. The largest share of freshmen (80.9%) enrol in

[12] Remedial undergraduate students cannot register for curricular exams before earning the OFA credits, with the sole exception of 3 credits in a foreign EU language. Only one in 168 remedial noncompliers earned the language credits, which explains the values reported in Table 3.

the examined undergraduate programmes after a standard schooling path, at the typical age of 18-19[13], whereas age is much more dispersed among later entrants (between 20 and 48 years of age). Late enrolment may depend on poor performance in early education, which leads to the late achievement of a secondary school diploma (15.1% of freshmen) and may signal a lower commitment to studying. However, late enrolment could also result from either voluntary or involuntary gap years between secondary and tertiary education (7.5% of freshmen), which may nonetheless condition learning capabilities when returning to formal education.

Language difficulties[14] or a disadvantaged social background may penalise students who are not EU-citizens. However, the impact of this variable is not immediately predictable at the sample university where non-EU students constitute a highly heterogeneous group that spans from recent immigrants who left their family and their country to register at university to socially and linguistically integrated Italian natives from foreign parents. A similar reasoning holds for the role of gender, because female students are reported to score better academic performance than male colleagues in the literature, yet traditional orientation towards non-technical disciplinary fields may require longer initial adaptation.

Independent variables that assess the proximity between university and student's residence (15.2% of enrolled students reside in the city where they attend university and an additional 68.8% reside in the surrounding province) aim at capturing advantages connected with lower commuting time, easier access to city-based cultural and social services, and closer family support. The last set of variables in Table 4 controls for cohort-fixed effects and outlines the progressive increase in the number of enrolled freshmen, witnessed by the higher share of students in more recent cohorts.

4. Empirical outcomes

4.1. The effectiveness of remedial courses

Tests based on Student t and Pearson chi2 statistics verified the non-random distribution of the identified predictors of academic performance between remedial and nonremedial students. Accordingly, an IPWRA doubly robust estimator that accounts for the stronger concentration of risk factors among remedial students seems suitable to test the research hypothesis. In particular, this study employed the IPWRA estimator implemented in the teffects program in Stata 15 (StataCorp, 2017).

[13] In Italy regular students enter primary school in the fall of the year they become 6 years old and complete secondary school 13 years later, in the summer of the year they become 19 years old.
[14] Undergraduate programmes are typically lectured in Italian.

Before presenting the results of the IPWRA estimates Table 5 reports the outcomes of a logistic model that assesses the impact of pre-treatment covariates on the probability of failing the admission test. The sign and the significance of the coefficients reflect outcomes consolidated in the literature. The marginal effects in Table 5 show that the single most important factor affecting the outcome of the admission test is attendance of a scientific lyceum during high school years, followed by the grade received from the high school final exam. Compared to the residual category of "Other types of high school", a diploma from a scientific lyceum reduces the probability of assignment to a remedial course by 36.1%, whereas a 10-point increase in the 100-point grade of the high school final exam involves a 9.4% decrease in the probability of assignment to a remedial course.

[Table 5 about here]

Table 6 summarises the estimates of the causal effect of assignment to a remedial course on the academic performance of successful remedial students. All estimates are replicated for the whole sample of new entrant students (*i.e.*, remedial and nonremedial students, for whom results are reported in the first column) and for the sub-sample of remedial students and nonremedial Poor starters (second column). For comparative purposes each panel in Table 6 focuses on a specific outcome variable (Credits1, Credits2, and DropOut2, respectively) and includes the outcomes of three different models. The first model is a basic unweighted OLS or logit regression of the outcome variable on two interacted binary variables that signal assignment to the treatment and successful exit from the remedial status[15], controlling for the covariates in Table 4. Table 6 reports the coefficient that captures the causal effect of successfully completing a remedial course conditional on assignment to the treatment. The two following models account for non-random assignment to a remedial course by implementing IPWRA doubly robust estimators. The second model follows what Imbens and Rubin (2015) define a naïve approach to noncompliance, the so-called "per protocol" approach, which simply discards all observations of remedial students who do not comply with the assignment of acquiring the extra OFA credits. In this case the ATET parameter is supposed to directly assess the effect of the receipt of treatment on compliers, who are the only treated individuals included in the estimate. Provided estimates risk nevertheless to be biased because despite discarding manifest noncompliers they still include latent noncompliers, *i.e.*, members of the control group who would reject the

[15] Those two indicators overlap for the outcome variable DropOut2, because all remedial students who continue in the same undergraduate programme beyond the second year manage to earn the OFA credits.

treatment in case of assignment. Eventually, the third model accounts for noncompliance by applying the IPWRA approach to compliers and noncompliers and calculating the ATET and the CACE parameters. In this case the ATET parameter represents the so-called intention-to-treatment, *i.e.*, the average causal effect of assignment to the treatment independently of the actual receipt of treatment itself (Imbens and Rubin, 2015). The causal effect of compliance with the assigned treatment is rather measured by the CACE coefficient, which focuses on remedial students who pass the exam at the end of the remedial course. After estimating the ATET the CACE coefficient is calculated based on equation (5) above, under the hypothesis that noncompliant students will earn zero credits, when the outcome variable concerns cumulated credits, and will be forced to drop-out from the undergraduate programme by the end of the second academic year, when the outcome variable is DropOut2.

[Table 6 about here]

Estimates in Table 6 offer three key results. First, from a methodological point of view the comparison between basic regressions and IPWRA regressions shows that OLS (logit) regressions provide significantly biased estimates due to the non-random distribution of characteristics that affect selection into treatment and outcomes across treated and control individuals. In particular, OLS regressions overestimate the credit loss suffered by compliant remedial students compared to the control groups, whereas logistic regressions overestimate the drop-out rate of those students. In line with expectations, even if to a lesser extent, also IPWRA estimators based on the per protocol approach underestimate the performance of successful remedial students. The adoption of a methodological approach able to account for both non-random assignment to the treatment and non-compliance in treatment receipt is therefore necessary to provide an unbiased assessment of the causal effect of remedial courses characterised by test-based entry and exit rules.

Second, the causal effect of successfully completing a remedial course depends on the chosen outcome variable. The CACE coefficient is always negative and highly statistically significant when it measures the differential in the credits earned by successful remedial students compared to their potential outcome under no treatment. However, the negative credits differential measured by the CACE grows less than proportionally when measured along a two-year period compared to a one-year period (and gets non-statistically different from zero when the control group includes Poor starters only). In addition, the CACE parameter is never statistically significant when the outcome variable is the two-year drop-out rate. Contrasting signals from a range of complementary indicators are not surprising given the multi-faceted nature of the academic performance and the distinctive learning and maturation processes lived by tertiary education students in different phases of their path. The outcomes in Table 6 rather reinforce the need for assessing the effectiveness of remedial courses based on parameters that address different dimensions of the academic performance in different moments of the academic career.

The third key outcome from the estimates in Table 6 concerns the choice of the reference group to gauge the progress of remedial students. When comparing students who successfully complete the remedial path with the full control group the statistical significance of the CACEs for Credits1 and Credits2 remains high. However, when the control group focuses on non-remedial Poor starters the estimated CACE displays a lower statistical significance in the case of variable Credits1 and becomes not statistically different from zero for the credits accumulated in two academic years. This outcome outlines a substantial challenge for admission tests and remedial courses manages, which concerns the identification of satisfactory performance levels for both remedial and non-remedial students and of the support actions to be activated accordingly.

Overall, outcomes in Table 6 offer only partial support to the research hypothesis. After accounting for the non-random distribution of confounders among the observed students and for the different behaviours of treated compliers and noncompliers the two-year drop-out rate displays no significant difference between the observed performance of remedial compliers and the counterfactual potential outcome. When the outcome variables measure accumulated credits the provided estimates offer some evidence of catch up with the weakest non-remedial students, but differences with the average performance of students who passed the admission test remain substantial and significant.

4.2. Underlying hypotheses and robustness checks

All statistical approaches aimed at solving the problem of non-random distribution of propensity to treatment by individuals in the treatment and in the control group base on three underlying assumption on data, namely the independent and identically distributed sampling assumption for the treatment status and the outcome variable of interest, the conditional-independence assumption between outcomes and treatment assignment, and the overlap assumption. Independent and identically distributed random variables are mutually independent and present the same distribution across the observed population. Accordingly, the independent and identically distributed sampling assumption requires that the treatment status and the outcomes of each individual in the sampled population are independent from the values observed for other individuals and that each individual has the same probability of participating in treatment or achieving a certain outcome level. In the examined case the identical distribution of the treatment assignment and the observed output is ensured by the randomisation process based on the inverse probability weighting procedure, whereas the mutual independence of key variables is ensured by the formality of the processes that govern students' academic career. For one thing, assignment to the treatment is based on an individual standardised and objective test evaluated by a third-party organisation. For another, curricular credits (the driver of all measures of academic performance) are acquired by means of exams that in undergraduate programmes in engineering almost exclusively involve individual tests on subjects that allow for quantitative, objective assessment.

The conditional independence or unconfoundedness assumption states that "adjusting treatment and control groups for differences in observed covariates, or pre-treatment variables, removes all biases in comparisons between treated and control units" (Imbens and Wooldridge, 2009, p.7). An overidentification test for covariate balance based on the weights calculated by the IPWRA estimators (Imai and Ratkovic, 2014) allows to largely accept the null hypothesis of balanced covariates for all provided estimates.

Eventually, the overlap assumption requires that for each given value of the covariates both treated and controls can be observed. In other words, each treated individual has a positive probability of not being assigned to the treatment, and vice-versa. Visual inspection of the density functions of the probability of treatment for treated and control individuals confirmed no violation of the overlap assumption for all provided estimates.

The model specification adopted to estimate the causal effect of remedial courses further assumes that no unobservable variable affects both the probability of selection into treatment and the potential academic outcome. A Wald test to identify non-null correlations between the treatment model and the outcome model allowed to rule out risks of biases in provided estimates due to endogeneity between the assignment rule and the potential outcome.

The last robustness check explores how changes in the definition of Good starters and Poor starters affect the estimates outcomes. In the right-hand estimates of Table 6 the control group is limited to nonremedial students who scored at most 120% of the entry test cut-off. In the case of the two-year drop-out rate the composition of the restricted control group cannot affect the judgement on the causal effect of remedial courses, because the differential outcome of successful remedial students is not statistically different from zero also when the control group includes all nonremedial students. However, in the case of outcome variables that measure the number of earned credits the differences in the significance of the CACEs when the control group includes either all nonremedial students or Poor starters only suggest the opportunity of a sensitivity analysis to assess up to what limit successful remedial students manage to catch up with less prepared nonremedial students.

Table 7 reports the estimates of the CACE parameter for outcome variables Credits1 and Credits2 when the best performance that identifies Poor starters increases from 110% to 150% of the entry test cut-off score. When academic performance concerns the credits accumulated in the first academic year successful remedial students manage to catch up only with nonremedial students who scored no more than 10% above the minimum floor. In contrast, in the case of the outcome variable Credits2 the performance of successful remedial students is non-statistically different from nonremedial students who scored up to 30% above the same cut-off. This set of estimates confirms that the performance of successful remedial students improves in time. However, it also confirms that, also when successful, in terms of earned credits remedial students manage to catch up at most with the lowest tail of nonremedial students, risking significant delay in graduation time.

5. Discussion and concluding remarks

The increasing heterogeneity of students enrolling in tertiary education calls for new solutions to provide all candidates with the skills and knowledge levels that enable the achievement of the desired certificates. The adoption of screening tools to restrict entry to the best promising students is not an option, not only because larger participation in tertiary education reflects the policy choice of easing the access to high-profile careers. More graduates and post-graduates are required to support the development of a technology-intensive and knowledge-intensive society and this is especially true for graduates from the STEM fields. However, remedial education is costly, it takes resources away from support and development initiatives targeted to other worthy groups of students, and return to investment becomes visible only in the medium-to-long run. The empirical assessment of the measurable effects generated by existing initiatives would consequently provide valuable advice to design and adjust ongoing projects.

The analysis provided in this paper concerns remedial courses in mathematics offered to newly enrolled undergraduate students in industrial engineering. The examined remedial courses are governed by an assessment-based assignment rule and an exit rule including a binding exam that, if not passed, blocks the development of the academic career. This empirical setting is particularly interesting because it reproduces the conditions of an increasing number of remedial courses in Italy and in the EU. In addition, the examined remedial courses are intensive enough to prospect nontrivial impact on the mathematical preparation of the exposed students.

Based on doubly robust IPWRA estimators, the empirical analysis has shown that remedial courses in mathematics succeed only partially in supporting catch up with better endowed students. Successful remedial students catch up with nonremedial students in two-year retention rate. However, the latter always outperform remedial students in credits earning. When students who remediate successfully compare to a restricted control group of nonremedial students who scored between 100% and 120% of the admission test cut-off also the difference in earned credits becomes statistically non-significant by the end of the second academic year.

With the implementation of procedures that connect public financial support to universities to the assessment of teaching and research performance by the National Agency for the Evaluation of Universities and Research Institutes, the academic staff of Italian universities has experienced a growing pressure to improve students' academic performance. Under this perspective, catch up of successful remedial students with Poor starters, whose performance is far from acceptable standards (*e.g.*, 39.2 credits earned in two years out of the standard 120 ones, and a 20.1% drop out rate after two years), cannot be regarded as a satisfactory outcome.

The academic staff at the university department that manages the examined undergraduate courses has been exploring alternative solutions, which include more intense orientation efforts and the redesign of remedial initiatives. Orientation efforts involve improved communication with candidate students and local high schools, to encourage early choice of the undergraduate course and better focused preparation in the final years of the secondary school. However, orientation efforts also involve initiatives targeted to under-prepared students, to raise awareness of their learning needs and, when appropriate, favour early transfer to better promising academic tracks. The redesign of remedial courses includes a more moderate use of (expensive) face-to-face classes in favour of a more intense resort to on-line resources and e-tutoring; the anticipation of support initiatives before the beginning of the academic year, to limit overlapping with other lectures; and the extension of participation to a wider share of students in the lower tail of the admission test scores.

The proposed analysis presents some limits that should be addressed by future research. First, focus on the specific disciplinary field of industrial engineering constrains the generalisation of the findings (Kokkelenberg and Sinha, 2010). Second, personal interests, and vocational interests to a larger extent, are important predictors of performance both at work and in the education system (Nye *et al.*, 2018). Since interests are also correlated with other drivers of academic success such as cognitive ability and socio-economic characteristics, their omission may result in significant biases of the provided estimates. Accordingly, further research may take into account student personal interests, for instance by complementing administrative data with information from questionnaires administered to enrolling students.

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Table 1. Performance indicators for undergraduate programmes in industrial engineering: Sampled university vs. Italy

	Sampled university			Italy		
Academic year	2014-15	2015-16	2016-17	2014-15	2015-16	2016-17
Average credits in first academic year to curricular standard [%]	33.7	37.9	33.9	49.2	52.5	52.7
Percent of students who enrol in the second academic year with at least 20 credits [%]	45.1	48.3	41.3	59.0	62.1	60.1
Percent of true freshmen who graduate in the initial curriculum within 4 years [%] [(a)]	39.6	43.2	42.1	38.5	39.5	41.1

Source: ANVUR (Italian National Agency for the Evaluation of Universities and Research Institutes)
[(a)] Standard duration of curricula equal to three years

Table 2. Correlation rate among output variables

Variable		Credits1		Credits2		Grad4		GradGrade	DropOut2
Description		Credits earned in 1st academic year		Credits earned in 1st and 2nd academic years		Diploma in up to 4 years		Certificate grade	Drop-out within 2nd academic year
Credits1	Pearson Corr.	1.000							
	N	2,344							
Credits2	Pearson Corr.	0.722	***	1.000					
	N	1,512		1,515					
Grad4	Pearson Corr.	0.408	***	0.705	***	1.000			
	N	873		704		703			
GradGrade	Pearson Corr.	0.081	***	0.384	***	0.255	***	1.000	
	N	493		493		493		493	
DropOut2	Pearson Corr.	-0.421	***	-0.390	***	-0.414	***	(a)	1.000
	N	1,819		1,539		1,343		493	1,819

**** Correlation is significant at the 0.01 level (2-tailed); (a) Cannot be calculated because no graduate drops out*

Table 3. Output variables by performance in the admission test

	Credits1 [(b)]			Credits2 [(c)]			DropOut2 [(c)]	
	#	Mean	Std. Dev.	#	Mean	Std. Dev.	#	%
All freshmen	2,341	19.032	20.917	1,512	46.371	36.448	1,819	23.7%
All freshmen with test	2,255	19.364	20.960	1,445	46.831	36.423	1,733	22.7%
Remedial students - Non compliers	168	0.018	0.231	56	0.000	0.000	116	100.0%
Remedial students - Compliers	386	10.811	13.876	241	30.983	28.369	291	26.5%
Non-remedial students - Poor starters	661	16.375	18.915	447	39.235	31.758	547	20.8%
Non-remedial students - Good starters	1,040	27.563	22.220	701	60.864	36.360	779	11.0%
No test [(a)]	86	10.326	17.749	67	36.448	35.838	86	45.3%

[(a)] Not included in econometric estimates; [(b)] Cohorts 2012-2016; [(c)] Cohorts 2012-2015

Table 4. Drivers of assignment to remedial courses and academic performance: Descriptive statistics

Variable		**N**	**Mean**	**Std. Dev.**
High school final grade [/100]		2,481	77.376	10.875
			%	
High school type	Scientific Lyceum	2,311	49.3	
	Other type of Lyceum	2,311	5.0	
	Technical high school, Technology	2,311	22.8	
	Other type of Technical high school	2,311	11.9	
	Vocational high school, Technology	2,311	5.9	
	Other type of high school [(a)]	2,311	5.1	
Undergraduate programme	Automation engineering [(b)]	2,333	16.4	
	Mechanical engineering [(b)]	2,333	48.5	
	Management engineering [(a)] [(b)]	2,333	35.1	
Late achievement of secondary school diploma		2,333	15.1	
Time gap between secondary and tertiary education		2,333	7.6	
Non-EU citizen		2,333	5.7	
Female student		2,333	18.0	
Residence	Residence in university province	2,333	68.8	
	Resident in university city	2,333	15.2	
Cohort fixed effects	Cohort 2012-13	2,496	18.5	
	Cohort 2013-14	2,496	18.9	
	Cohort 2014-15	2,496	20.1	
	Cohort 2015-16	2,496	20.7	
	Cohort 2016-17 [(a)]	2,496	21.8	

[(a)] Reference category in econometric estimates [(b)] Post-treatment variables in outcome regression only

Table 5. Marginal effects of predictors of student performance on assignment to a remedial course

Covariate	Marginal effect	Delta-method Std. Err.	z	
High school final grade	-0.009	0.001	-12.29	***
Scientific Lyceum [(a)]	-0.361	0.029	-12.54	***
Other type of Lyceum [(a)]	-0.162	0.042	-3.87	***
Technical high school, Technology [(a)]	-0.121	0.031	-3.94	***
Other type of Technical high school [(a)]	-0.073	0.033	-2.21	**
Vocational high school, Technology [(a)]	-0.078	0.037	-2.10	**
Non-EU citizen	0.057	0.020	2.78	***
Female student	0.075	0.027	2.75	***
Late achievement of secondary school diploma	0.125	0.031	3.98	***
Time gap between secondary and tertiary education	0.116	0.021	5.44	***
Resident in university city [(b)]	-0.092	0.028	-3.24	***
Residence in university province [(b)]	-0.048	0.021	-2.32	**

*Logit regression. Dependent variable: assignment to a remedial course. Cohort-fixed effects included. N=2,237. Pseudo R2=0.257. Correctly classified cases: 80.3%. *** p< 0.01 ** p< 0.05*
Reference category: (a)=Other type of high school; (b)=Residence outside university province.

Table 6. The causal effect of successfully completing a remedial course on remedial students' performance

Outcome variable	Model	Parameter that captures the researched causal effect	All students			Poor starters + Remedial students		
			Coef.	*Std. Err.*		*Coef.*	*Std. Err.*	
Credits1 [No.]	OLS regression	Marginal effect of compliance	-7.714	0.886	***	-4.527	0.931	***
	IPWRA, per protocol	ATET	-6.516	0.931	***	-3.711	0.976	***
	IPWRA, all observations	CACE	-4.805	0.998	***	-2.039	1.024	**
Credits2 [No.]	OLS regression	Marginal effect of compliance	-11.238	2.082	***	-5.792	2.240	***
	IPWRA, per protocol	ATET	-9.773	2.188	***	-4.430	2.368	*
	IPWRA, all observations	CACE	-7.248	2.314	***	-1.791	2.509	
DropOut2 [%]	Logit regression	Marginal effect of compliance	17.0%	0.020	***	20.5%	0.028	***
	IPWRA, per protocol	ATET	7.0%	0.032	**	6.3%	0.035	*
	IPWRA, all observations	CACE	5.4%	0.040		5.0%	0.043	

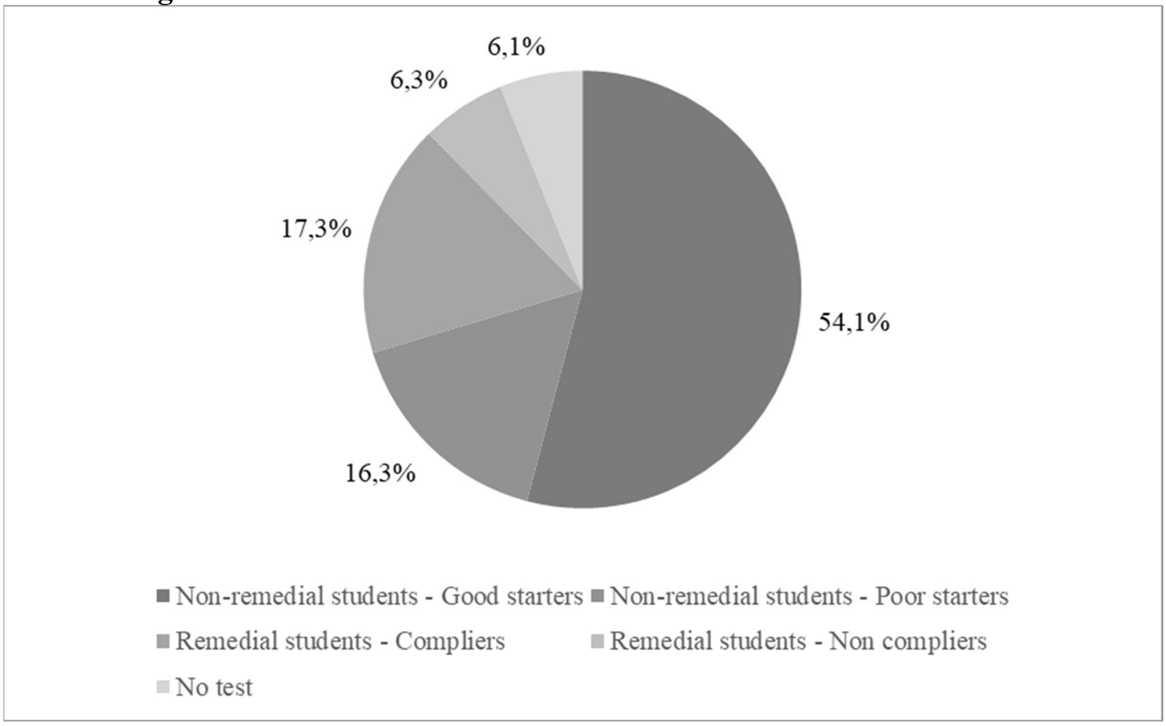
ATET: average treatment effect for the treated; CACE average causal effect for compliers
**** p< 0.01 ** p< 0.05 * p<0.10*

Table 7. Change of the CACE with change in the top performance of Poor starters' control group in the entry test

Poor starters' top performance in the entry test	Credits1						Credits2					
	CACE				*No. Obs.*		*CACE*				*No. Obs.*	
	Coef.	*Std. Err.*	*z*	*P>z*	*Remedials*	*Nonremedials*	*Coef.*	*Std. Err.*	*z*	*P>z*	*Remedials*	*Nonremedials*
Max 110% of cut-off point	-1.516	1.097	-1.38	0.167	553	465	-0.223	2.606	-0.09	0.932	294	328
Max 115% of cut-off point	-1.945	1.064	-1.83	0.068	553	574	-1.844	2.581	-0.71	0.475	294	388
Max 120% of cut-off point *	-2.039	1.024	-1.99	0.046	553	659	-1.791	2.509	-0.71	0.475	294	438
Max 125% of cut-off point	-2.363	1.010	-2.34	0.019	553	749	-2.520	2.504	-1.01	0.314	294	495
Max 130% of cut-off point	-2.759	0.984	-2.80	0.005	553	838	-3.798	2.434	-1.56	0.119	294	555
Max 135% of cut-off point	-3.460	0.970	-3.57	0.000	553	926	-4.975	2.404	-2.07	0.039	294	613
Max 140% of cut-off point	-3.558	0.963	-3.70	0.000	553	1,009	-5.540	2.376	-2.33	0.020	294	667
Max 145% of cut-off point	-3.517	0.955	-3.68	0.000	553	1,086	-5.352	2.355	-2.27	0.023	294	717
Max 150% of cut-off point	-3.660	0.955	-3.83	0.000	553	1.154	-5.610	2.361	-2.38	0.018	294	757

** Definition adopted for estimates in Table 6*

Figure 1. Performance in the admission test – Cohorts 2012-2016



Non-remedial Good starters score above 120% of the cut-off in the entry test; Non-remedial Poor starters score between 100% and 120% of the cut-off in the entry test; Remedial Compliers fail the entry test and successfully complete the remedial course; Remedial Noncompliers fail the entry test and the remedial course exam.