Selective Admissions and Freshmen's Academic Outcomes

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Abstract

Italian higher education system has been suffering from high college drop-out rates for almost three decades and has undergone some significant education reforms during the 1990s and early 2000s. Yet Italy still has one of the highest college drop-out rate among the OECD countries. After the failure of last reform, which is known as "Bologna Process", some universities have started to carry into execution some ex-ante selection procedures in order to admit more high-performing students. This paper aims to provide an evidence on the causal effects of selective admission test on the academic outcomes of freshmen by exploiting a unique administrative data from Universita Cattolicà del Sacro Cuore which is a leading private university based in the North of Italy. Employing a difference-in-differences approach, our main findings suggest that the introduction of the admission test reduces the drop-out rate of first year students on average about 2.5% and increases the average credits about 5.00 point. We support these results by running several placebo diff-in-diffs regressions using the pre-treatment years in our data. We also show the changes in observable characteristics of students after the policy change and moreover we look at the heterogeneous effects of the test on low-ability students' academic outcomes and found that the selection procedure is even more beneficial for the low-ability students. Finally, using the information on the test-scores of students we provide some insights on the effects of the selection procedure's components, and the results show that only the mathematic section has a significant effect on the reduction of drop-out rates.

JEL codes: I21, I28, C21

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1 Introduction

Participation in higher education has always attracted a lot of attention from the economists and policy makers since the human capital accumulation, needless to say, takes a very important place in nations' economies. One important topic in the higher education literature, therefore, is the selective policies on access to tertiary education institutes and their effects on both students' academic performances (i.e. drop-out rate, grade points) and their future prospects (i.e. wage). In this paper, we look at the effects of selective admission test and provide an updated evidence on the subject by exploiting a unique administrative data-set from a large private university in which located in the North of Italy. Our aim is pin down the causal effect of the selective admission test on two different educational outcomes of first year students: drop-out rates and average credits.

College drop-out is a world-wide growing concern and is often considered as a social problem. Drop-out decision most of the time is driven by the overconfident students who think that they are capable to complete a college degree program in the first place. Although there are other reasons can cause a drop-out decision (i.e. the educational environment may not meet with the expectations of students or unexpected situations occurred in student's family etc..), overconfidence students can be considered as the real “trouble-makers". When a student withdraws his college enrollment, he happens to waste resources of the related university for the academic years he participated in. Moreover, families invest in their children's future by covering their living expenses and, if required, by paying the tuition fees through the time their children stay in college. Hence, after a drop-out decision all those investments will go wasted and can affect the welfare of families. As for the student who makes the drop-out decision, since he delays his labor market participation during his studentship years, when he initiates his career in labor market without completing his degree he will start from behind of his era and this might have long-term effects on his career. They also contribute to the labor market with bad entry and carry a bad signal to the market.

It has been an important discussion topic for many years how governments should take an action to decrease the college drop-out rates in their countries. Italy is a one specific case in which the college drop-out rate is one of the highest among OECD countries. Italian higher education system has undergone several reforms since the late 1980s to deal with this issue. The most recent one, which is known as “Bologna Process", has been in force since 2001 and is specifically designed to reduce the college drop-out rates[1]. Although this reform has evidently increased the university enrollment rates, this increase has not necessarily been followed by a raise in graduation rates (Bratti 2008). Since the latest reform has also failed to decrease the college drop-outs, Italian Minister of Education required all universities to perform an ex-post selection procedure in 2010. According to this procedure, students have to pass a test after they are admitted to university but even they do not pass the test at first they can always take the test next year until they obtain the necessary score and of course this type of selection process would not change the outcome either. Therefore, some of the universities have started applying ex-ante selection procedures such as performing compulsory selective admission tests to receive more high-ability students.

Selective admission tests can improve the academic outcomes of students through two main channels. First one is the composition effects which can be explained through two inner-channels: the signal sent by the university via the announcement of the selective test and the improvement in the observable characteristics of the students. Having a restricted access to the university is a statement of promising a better educational environment to the applicants and can attract more students with high-ability to apply for the related departments. Thus we can expect to observe some improvements in the students' characteristics (i.e. students graduated from high-schools with better grades). Moreover, once a student is told that he is good enough to be admitted to the university, this student will be self-motivated and perform better during his academic life. Second channel that selective admission test can affect the academic outcomes is the interactions among students which is called “peer effects". Students share information

[1]See Cappellari and Lucifora 2009; Di Pietro 2008; Bratti 2008 for detailed information on Bologna Process.

with each other about their classes, courseworks and exams during an academic year and there are several studies show that the more students have better peers the better they perform[2]. Since the selective admission test provides a better student profile and creates a better educational environment for students, this will have a positive impact on the academic outcomes of students in the end.

There is a substantial literature on the effects of admission tests but the evidence is rather mixed. Some studies have shown that selective admission test plays an important role to predict students' performances and persistence (Park and Kerr, 1990; Bridgeman et al. 2004; Noble et al. 2005), while some others have pointed out the importance of the high-school graduation marks and found that admission test is meaningful only when high-school graduation marks are taken into account (Burton and Ramist, 2001; Cohn et al. 2004; Ragan et al. 2011). Geiser and Santelices 2007, on the other hand, have stated that high-school graduation marks are still the best predictor for the students' academic outcomes.

Besides the correlational studies, there are two important studies similar with our work in this paper where the causal effects of selective admission test on academic outcomes is estimated by applying diff-in-diffs approach. Carrieri et al. 2015 have shown that introduction of the selective test reduces the drop-out rate of first year students about 14% and increases the average grades 0.78 point by using a data from a large public university in which located in the South of Italy. The corresponding university in their study, however, has $35 - 40\%$ average drop-out rate for the first year students. This number is almost two times more than a national average which is around $15 - 20\%$ and thus the effect of admission test they estimate is quite large as well. Their result is upper-bond and may not reflect the real situation in Italian higher education system. One possible explanation for this result, when the unemployment rate is high, more low-ability students rather apply for the universities than stay unemployed and, hence, the drop-out rate is scaled up.

Francesconi et al. 2011, on the other hand, did not find statistically significant effect of

[2]See Hoxby 2000; Sacerdote 2001; Zimmerman 2003; Pischke and Ammermueller 2009; De Paola 2010.

an admission test on graduation rate for the same university (Università Cattolica) we are investigating in this paper. Università Cattolica had performed selective admission tests during the 1990s but after an opening of a new public university in Milan in the mid-1990s, Università Cattolica faced with a significant decrease in demand and abrogated this selection procedure afterwards. The lack of demand reduces the efficiency of the admission test and this explains the results of Francesconi et al. 2011 for why they did not find any effects through the implementation of selective admission test.

In the present paper we estimate the effects of selective admission test on drop-out rates and average credits of first year students enrolled in Economics Department of Università Cattolica del Sacro Cuore which is the largest private university in Italy. We employ a difference-in-differences approach in order to capture the causal effects of this new selection procedure. Economics is the only department started performing the test since 2012/13 academic year. This situation, therefore, allows us to apply a complete DID and estimate the changes in academic outcomes of interest between treatment and control groups after the policy change. Our main findings show that this new policy reduces the drop-out rate of first year students about 2.25% on average and increases the average credits taken by the first year students around 5.13 points on average. As already have stated above, the main reason our results contradict with the ones of Francesoni et al. 2011 is the increase in demand of students over the years. Although the average demand has been declining in Italy since 2005, the situation is opposite for the Universitá Cattolica and demand has been steadily increasing. On the other hand, our findings are consistent with the results of Carrieri et al. 2015 but in a more realistic way. Since the average drop-out rate of first year students is around $10 - 12\%$ in the Università Cattolica which is a bit lower yet similar to the nation average–it is known that private universities tend to have less of a drop-out rate than the total average–, our treatment effects are smaller in magnitude as well compared to the results of Carrieri et al. 2015. We support the robustness of our results by running several placebo DID regressions which shall be discussed later on this paper.

In addition to our main findings we also look at the effects of admission test on the high-school graduation marks and we observe an average increase of 2.5 points after the reform. This increase in high-school final marks of students is a sign that after the policy change more high-ability students started being admitted to the Economics which is one of the working mechanism of the selective admission test as previously explained.

We also estimate the heterogeneous effects of admission test on the low-ability students' academic outcomes and our results suggest that policy change is more beneficial for the low-ability students by reducing their drop-out rate around 5% on average. This result is mostly linked to the potential peer effects which is described as the second channel of how admission test functions. Once low-ability students have better peers around them they perform better, however, it is worth to note that this increase in low-ability students' academic performance is also related to the fact that they are told to be good enough to enroll in corresponding department since they passed the selective test, which may have an impact on their performance as well.

Finally, we provide some insights on the effects of the selection procedure's determinants on drop-out rates for the academic year 2013/14, which is the second year of the reform. The new selection procedure is a combination of admission test and high-school scores (the detailed information about the procedure can be seen below) of students, and our findings suggest that the test-score is the dominant component in terms of effecting the drop-out rates. A one unit increase in the standard deviation of test-score reduces the drop-out rate about 2.3%. Even more, we show that the entire effect of the test-score is coming from the mathematic scores of students, while other sections of the test do not have any statistically significant effect on drop-out rates.

Rest of the paper is organized as follows: in section-2 detail information about the data is provided along with some descriptive statistics; section-3 involves the identification strategy and the econometric models; we display the results in section-4; and final conclusions stated in section-5.

2 Data and Descriptive Statistics

We use an administrative data-set from Catholic University of Milan (*Università Cattolica del Sacro Cuore*) spanning the academic years from 2010/11 to 2013/14. Università Cattolica is the largest private higher education institute in Italy and has 5 campuses across the country: Milan, Piacenza, Brescia, Cremona and Rome. Our analysis in this paper, however, focuses only on the students based in Milan campus, in which the university is originally located, in order to obtain results without affected by the unobserved campus heterogeneity. Our working sample covers 18858 observations of first year students enrolled in Università Cattolica through the relevant academic years stated above. The data contains also some information on the observable characteristics of individuals (age, gender, surname) and information on the students' secondary school background (type of graduated high-school and the location of graduated high-school).

Economics is the only department in Universià Cattolica has been performing the selective admission test since 2012/13 academic year. This allows us to apply a complete difference-in-differences approach and to capture the effects of this policy change on the students' educational outcomes. In order to do so, students enrolled in Economics Department define our treatment group, while the students admitted in other 7 departments (Banking and Finance, Law, Political Sicience, Linguistic, Psychology, Philosophy, Education) define the control group. We can thus apply “before-after" analysis for these groups.

To be eligible to enroll in Economics, first, all applicants must take the admission test. The test lasts one hour and covers 4 different sections: mathematics, logic, general culture and foreign language. All sections are equally weighted and for each section there are 12 questions which are prepared as multiple choice questions. The second component of the selection procedure is the student's performance during the last two years of his high-school education.

By taking into account of the grades that student obtained during his last two years in high-school, a “high-school score" (not high-school final mark) calculated by the administrative office of the university. In the end, the sum of 60% of student’s test score and 40% of his high-school score has to pass 40.00 to be admitted to the Economics. In the first year of the test, academic year 2012/13, approximately 1600 students were accepted out of 2000 applications, and in the second year of the test, academic year 2013/14, the number of students enrolled in Economics is about 1700 out of 3000 applicants.

One important complication should be noted about the first year of the test. In 2012/13 academic year 159 students were admitted in Economics Department even though their test and high-school scores combination was not high enough; moreover, 278 students who enrolled in Economics in that year did not take the test at all. This was totally unexpected and random situation. It was the initial year of the procedure and the process was new for both the department and students. As a result, this 437 students ended up in our treated group but without receiving the treatment–admission test– and we decided to exclude these students from our analysis. One might think of to place these students in control group rather than omitting them, however, the interaction between these students and the treated ones could affect the academic outcomes of these 437 students. Furthermore, these students also received the “signal" sent by the university through the announcement of the test which makes them self-selected and different than the students in control group. Therefore, because of these two effects–signal and peer effects- considering these 437 students as controls could mislead us and cause to obtain biased estimations in the end.

2.1 Variables

In our analysis we are interested in two educational outcomes of first year students: drop-out rates and average credits. The importance of drop-out rate has been discussed in the previous section and it is the main outcome of interest in this paper. A student is considered as a drop-out if she does not renew her enrollment in her second year or if she officially withdraws her admission from the university. On the other hand, average credits can be considered as an intermediate outcome and as a measurement of the willingness of students to their subject. The more confident the students are with their subject, the more credits are expected to be taken. Students are allowed to take maximum 60 credits in their first year, and classes evaluated as zero-credit are not taken into account for the calculation of average credits. Figure 1 and Figure 2 highlight, respectively, average drop-out rates and average credits over the academic years across departments and the dashed line stands for the initial year of the policy change. As can be seen easily in Figure 1, Economics Department has the lowest drop-out rates in the treatment years compared with the other departments. However, this downward trend in Economics starts at the 2011/12 academic year and still the drop-out rate of Economics is the second lowest in that year after Psychology Department. This may call in question our treatment effect estimates because such a decrease after reform might be an outcome of an ongoing trend and our results might be overestimated by taking advantage of such movement. Therefore, we run several placebo regressions, which are going to be discussed in the following section, to make sure that our treatment effect estimations are robust and we clarify our findings. Average credits, in Figure 2, follow a relatively steady pattern on and around 40 credits line over the years for each department and we observe an increase in average credits after the reform for Economics Department. Nevertheless, we apply the same placebo procedures on the average credits as well and do the robustness check.

Table 1 displays the mean statistics of both outcome and control variables used in our econometric model, and in column 13–the last column named Diff-Diff– for each variable we exhibit the changes in mean differences between treatment and control groups after the implementation of admission test. With other words, column 13 shows the results of our diff-in-diff estimations when there is no control variable used. Drop-out rate of treatment group decreases from 9.6% to 6.4% after the reform while the drop-out rate of control group stays at the same level around 11%. A similar improvement is observed for average credits; average credits of treatment group increases about 5 points after the treatment and no important change observed on control group's average credits level during the treatment years.

As for the control variables, age takes a place in our model as a continuous variable. We also control for the gender of students using a dummy for being female. Our data holds variety of information on students' secondary-schools such as high-school graduation grades, type and area of high-school that student graduated from . We consider high-school final marks as a measurement of students' ability and use it to estimate heterogeneous effects of treatment on low-ability students which shall be discussed later in this paper. High-school final grades vary from 60 to 100 since students required to get at least 60 in order to graduate from high-school in Italian secondary education system. Average high-school final marks of treatment group is on the increase around 2 points after the policy change while we observe a small reduction around 0.5 points in control group's average high-school final marks. The type of graduated high-schools is categorized into 6 groups (Carrieri et al. 2015): professional, technical, scientific lyceum, classical lyceum, linguistic lyceum and others. Professional and technical high-schools are known as vocational secondary schools and the rest is called *liceo* type high-schools in Italy. The mean difference between treatment and control groups in terms of the proportion of students graduated from vocational high-schools decreases almost 9% on average during the treatment years. Improvement in observable characteristics of students, which in this case it appears in high-school final marks and in the fraction of students graduated from vocational high-schools, is one of the channels that the new selection procedure can affect the educational outcomes. These improvements will be more formally investigated in the next section.

Another important information our data holds is the self-reported annual family incomes of students. We set three stages as wealth constraints (Carrieri et al. 2015): if reported annual income is €15000 or less these families are considered as low-income families, if it is between

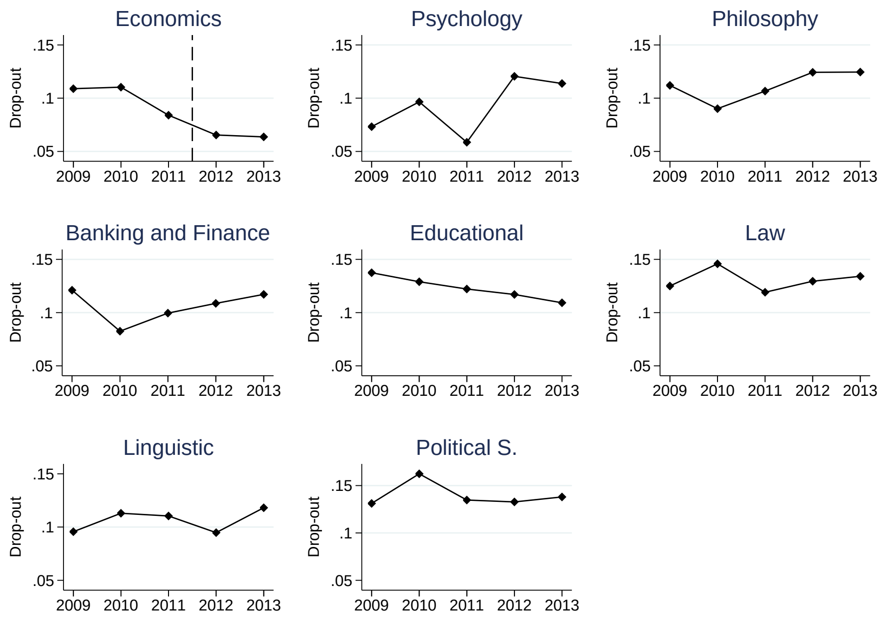

Figure 1: Drop-out rates of departments over years

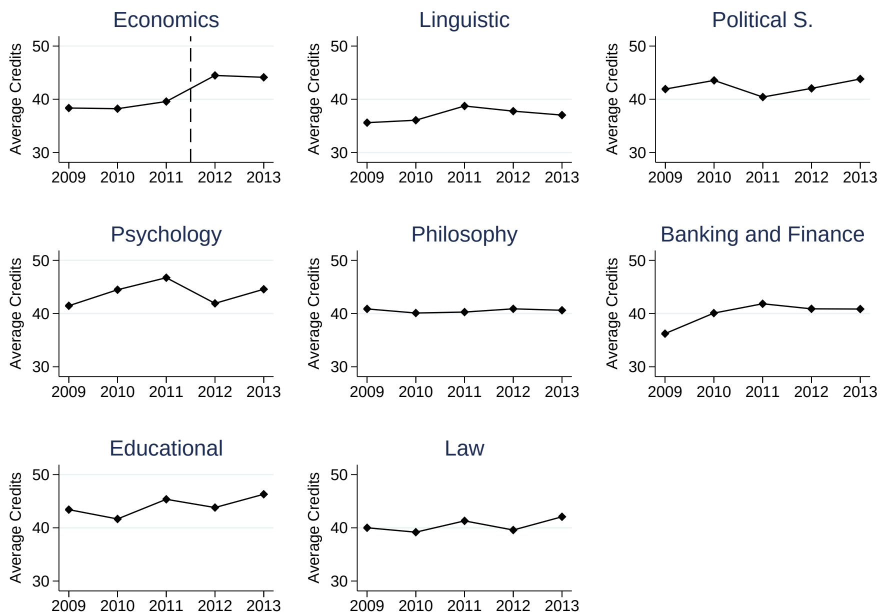

Figure 2: Average credits of departments over years

Variables	Definition	Before (2010/11 and 2011/12) Treatment	(S.D)	Control	(S.D)	Difference	After (2012/13 and 2013/14) Treatment	(S.D)	Control	(S.D)	Difference	Diff-Diff
Outcome Variables												
Drop-out	==1 if a drop-out	0.096	(0.295)	0.116	(0.320)	-0.019	0.064	(0.245)	0.118	(0.323)	-0.054	-0.035***
Average Credits		38.93	(16.90)	40.85	(17.01)	-1.913	44.26	(15.91)	41.13	(17.95)	3.129	5.043***
Individual Characteristics												
Age		19.63	(2.325)	19.90	(3.006)	-0.272	19.49	(2.157)	19.81	(2.682)	-0.320	-0.047
Gender	==1 if Female	0.414	(0.492)	0.714	(0.451)	-0.300	0.433	(0.495)	0.704	(0.456)	-0.270	0.030
Type of Graduated High-schools												
Professional	==1 if Profession	0.017	(0.130)	0.030	(0.170)	-0.012	0.011	(0.105)	0.037	(0.189)	-0.026	-0.013
Technical	==1 if Technical	0.243	(0.429)	0.180	(0.384)	0.062	0.195	(0.396)	0.209	(0.407)	-0.013	-0.076**
Science	==1 if Science	0.389	(0.487)	0.257	(0.437)	0.132	0.439	(0.496)	0.247	(0.431)	0.191	0.059*
Classical	==1 if Classical	0.182	(0.386)	0.250	(0.433)	-0.067	0.190	(0.392)	0.238	(0.426)	-0.047	0.019
Linguistic	==1 if Linguistic	0.020	(0.140)	0.044	(0.205)	-0.024	0.021	(0.145)	0.047	(0.211)	-0.025	-0.001
Others	==1 if Others	0.143	(0.350)	0.233	(0.423)	-0.095	0.138	(0.345)	0.218	(0.412)	-0.079	0.011
Areas of Graduated High-schools												
North-West	==1 if North-West	0.750	(0.432)	0.772	(0.419)	-0.022	0.754	(0.430)	0.782	(0.412)	-0.027	-0.005
North-East	==1 if North-East	0.061	(0.239)	0.055	(0.229)	0.005	0.068	(0.252)	0.050	(0.219)	0.017	0.012
South	==1 if South	0.095	(0.294)	0.089	(0.285)	0.005	0.087	(0.283)	0.076	(0.266)	0.010	0.004
Central	==1 if Central	0.039	(0.194)	0.039	(0.194)	0.002	0.040	(0.197)	0.047	(0.212)	-0.006	-0.007
Islands	==1 if Islands	0.053	(0.224)	0.042	(0.201)	0.010	0.049	(0.216)	0.042	(0.202)	0.006	-0.004
Self-reported Family Income												
Low-Income	==1 if ≤15000	0.012	(0.111)	0.012	(0.112)	0.000	0.104	(0.101)	0.016	(0.128)	-0.006	-0.006
Med-Income	==1 if 15000<x≤35000	0.145	(0.352)	0.182	(0.386)	-0.370	0.123	(0.328)	0.191	(0.393)	-0.068	-0.031*
High-Income	==1 if 35000<	0.841	(0.365)	0.804	(0.396)	0.037	0.866	(0.340)	0.791	(0.406)	0.074	0.037*
Other												
High-school F. M.		74.46	(10.40)	76.69	(11.66)	-2.235	76.46	(10.24)	76.08	(11.30)	0.379	2.614**
Stud/Teach	Number of students per Lecturer	5.652	(0.163)	4.324	(1.560)	1.328	11.20	(4.909)	8.765	(4.075)	2.440	1.112
Observations		2994		7439			2670		6800			

* p<0.10, ** p<0.05, *** p<0.01

Table 1: Descriptive statistics of variables

€15000 and €35001 we call them medium-income families and if the annual income is reported higher than €35000 they are labeled as high-income families. Students coming from wealthier families may be able to reach more sources (e.g. they can take private lessons or they can be less worried to repeat an academic year than other students) and tend to be more successful. By having these wealth constraints in our model, therefore, we aim to obtain treatment effect estimations without affected by the possible (dis)advantages that come from students' family-backgrounds.

To control class size effect, we use student teacher ratio (Carrieri et al. 2015); namely the number of students per lecturer at faculty level for each year. We are thus able to distinguish our treatment effect from the potential class size effects on students' academic performances since it has been evidently shown in the education literature that reduced form of classes has an efficacy on the academic outcomes of students (Kokkelenberg et al. 2008; Bandiera et al. 2010; De Giorgi et al. 2012).

Our data also holds information on the details of the selection procedure in academic year 2013/14. We have the scores of each section of the test (mathematics, logic, culture and foreign language), calculated high-school performances (high-school score) and total-scores (sum of 60% of test-score and 40% high-school score) of students. We shall report in results section some OLS regression results on drop-out rates by using this information to understand of which part of the new selective procedure plays a more important role on affecting drop-out rates.

3 Identification Strategy and Econometric Models

The implementation of selective admission test can affect the students' educational outcomes through two main channels. First, universities signal to the market through the announcement of the test. The signal sent by the university can attract high-ability students because high-ability students tend to choose more selective higher education institutions based on the idea that those highly selective institutions would provide a better educational environment

(Francesconi et al. 2011). As a result, we can expect to observe some improvements in the observable characteristics of individuals who exposed to selection procedure. Secondly, individuals' academic performances may evolve with the behaviour of the group that they interact with (Manski 1993). Although estimating peer effects is problematic due to reflection and endogeneity problems, there is a vast literature shows the importance of social interactions on educational outcomes.

As stated in the previous section, the Economics Department -our treatment group- implemented the selective test at the beginning of 2012/13 academic year. Students enrolled at Economics in 2012/13 and 2013/14 academic years exposed to new selection process while the students admitted to Economics in 2010/11 and 2011/12 academic years did not receive the treatment. Meanwhile, other 7 seven departments -our control group- have no such selective procedure in neither of those academic years. This situation thus enables us to estimate the causal effects of selective admission test on students' academic outcomes by comparing the differences in outcomes of treatment and control groups after and before the reform whilst controlling the unobservable but fixed effects at department level (Carrieri et al. 2015).

3.1 Baseline Model

We employ a DID set-up to estimate the causal effects of new admission policy of Economics Department on academic outcomes:

$$Y_i = \alpha + \gamma Econ_i + \lambda_1 T_{1,i} + \lambda_2 T_{2,i} + \delta_1 (Econ_i \times T_{1,i}) + \delta_2 (Econ_i \times T_{2,i}) + \beta X_i + \epsilon_i, \quad (1)$$

where Y_i represents the academic outcomes of interest of a student i, $Econ_i$ is the treated faculty dummy, $T_{1,i}$ and $T_{2,i}$ stand for, respectively, first and second treatment year dummies and X_i is the vector of controls – list of control variables is available in Table 1–, and the OLS estimates of δ_1 and δ_2 give us the treatment effects of first and second treatment years, respectively. We also take into account the possible inference problems may arise in our DID approach and produce robust and clustered standard error estimations. We have 92 (degree programs×years =23×4=92) clusters at degree program and academic year level.

3.2 Changes in Students' Secondary School Backgrounds

In this section we set a model to estimate the changes in students' high-school graduation marks and the types of high-schools they graduated from. The purpose of doing this is because we expect more students with high-ability after the reform which is one of the working mechanisms of the admission test and, therefore, given the high-school graduation marks as a measure of ability and the students graduated from *liceo* type of high-schools tend to perform better in their tertiary education, we are able to show the alteration of students' secondary school backgrounds.

Using the same econometric specification in Equation 1 we estimate the changes in high-school graduation marks after the reform. This time the outcome variable, Y_i, is the high-school final grade of student i, and for the controls age, gender, type and area of high-school are used. The rest remains the same as in Equation 1.

As for the type of high-schools, dependent variable, Y_i, is a binary variable which is equal to 1 if student i graduated from *liceo* type high-school (science, classical, linguistic, others) and it is equal to 0 if she graduated from vocational high-school (professional, technical). We apply logistic regression to estimate the probability of having a student graduated from *liceo* type high-school compared to having a student graduated from vocational type of high-school after the reform.

3.3 Placebo DID Designs

The baseline model described above, Equation 1, produces unbiased and consistent estimators under the similar trend assumption. According to this assumption, however, the outcomes of treatment and control groups would have followed a similar trend in the absence of treatment. Since one cannot possibly know that what kind of trend treatment group would have had in the absence of treatment, we do some robustness check to support our results in Equation 1 by using only the pre-reform academic years as if there was a policy change in some of those years. We use the same econometric specification used in Equation 1 but this time with different samples. Namely, given the Economics as treatment group and the other departments control group, we restrict our data from 2008/09 to 2011/12 academic years which are the years prior to the reform. Then we treat the students enrolled in Economics during the years 2010/11 and 2011/12 as if they were exposed to the treatment and estimate placebo treatment effects, δ_{1P} and δ_{2P}, as we do in Equation 1 to estimate real treatment effects. We repeat this process for three different samples by shifting backward the window of observation by one year.

Another placebo design we use to support our main findings in Equation 1 is as follows. Using all the academic years from 2006/07 to 2013/14 we estimate real treatment effects of 2012/13 and 2013/14 along with all the placebo treatment effects from 2007/08 to 2011/12 given the academic year 2006/07 as benchmark:

$$Y_i = \alpha + \gamma Econ_i + \sum_{k=2007/08}^{2013/14} \lambda_k T_{k,i} + \sum_{k=2007/08}^{2013/14} \delta_k (Econ_i \times T_{k,i}) + \beta X_i + \epsilon_i, \tag{2}$$

where all dependent and independent variables are the same with Equation 1 apart from the additional time dummies and their interactions with treated department dummy $Econ_i$. In Equation 2, we estimate the treatment effects in both absence and presence of the treatment at the same time and expect to have statistically significant estimators only for the coefficients of interaction terms that involve actual treatment years 2012/13 and 2013/14.

3.4 Treatment Effects on Low-Ability Students

We expand our baseline model and estimate the heterogeneous effects of selective admission test on a specific group of students, which we call low-ability students. By doing so, we compare the outcomes of students with similar ability but of students interacting with better peers since the selective test provides more qualified students (Carrieri et al. 2015). The estimations of heterogeneous treatment effects on low-ability students shed some light on the potential peer effects channel that admission test can affect the educational outcomes through.

Equation 3 is an extended version of Equation 1 which takes a place in the first line in Equation 3. In order to define the low-ability students, we use a dummy variable, Low_i, which is equal to 1 if student i's high-school final mark is 70 or less and is equal to 0 if the high-school final mark is higher than 70.

$$\begin{aligned} Y_i &= \alpha + \gamma Econ_i + \lambda_1 T_{1,i} + \lambda_2 T_{2,i} + \delta_1 (Econ_i \times T_{1,i}) + \delta_2 (Econ_i \times T_{2,i}) + \beta X_i + \epsilon_i \quad (3) \\ &+ \gamma_L (Econ_i \times Low_i) + \lambda_{1L} (T_{1,i} \times Low_i) + \lambda_{2L} (T_{2,i} \times Low_i) \\ &+ \delta_{1L} (Econ_i \times T_{1,i} \times Low_i) + \delta_{2L} (Econ_i \times T_{2,i} \times Low_i), \end{aligned}$$

where additional interaction terms in the second and third rows identify our heterogeneous treatment effect model and the OLS estimations of δ_{1L} and δ_{2L} give us the effects of admission test on the academic outcomes of low-ability students, respectively, for the first and second years of the treatment.

4 Results

4.1 Baseline Model

We present the results of our baseline model, Equation 1, in Table 2 and Table 3, respectively, without and with control variables. In the first columns we display the DID estimates for drop-out rates while the second columns show the results for average credits. As a starting point, in Table 2 we observe an average reduction of about $3,5\%((3.1 + 3.8)/2 = 3.45)$ in drop-out rates and 5.13 points ((5.80+4.46)/2=5.13) increase in average credits after the introduction of selective test. These results are in line of our initial expectations. The increase in the average credits after treatment is a sign of having students who are more confident with their degree programs than the students from pre-treatment years and this increase in average credits, thereby, is followed by a decrease in the drop-out rates because the more the students get involved in their courses, the less likely they will drop out in the end. Academic outcomes of students, however, may depend on their individual characteristics and family backgrounds. So, for that matter, in Table 3 we provide the results while several control variables are included in our model and still the new selection procedure decreases (increases) drop-out rates (average credits) on average about 2.2% (3.67 points). Although there is a reduction in volume of the treatment effect estimations for both drop-out rates and average credits, the treatment effects do not vanish away once the control variables are taken into account. That reduction is mostly caused by the first year treatment effect estimations and one possible explanation for having smaller estimates in the first year of the treatment is that the demand during the initial year of reform fell short of the expectations. As previously stated, 1600 students were admitted to the Economics Department in academic year 2012/13 out of only 2000 applications while this number increased to 3000 applications in the following year. The lack of demand might have lessened the efficiency of selective test and as a result we might end up having smaller effects from the first year compared to the second treatment year. Also, for neither of which outcomes of interest the first year treatment effect estimations are statistically significant, however, the standard errors of related coefficients are in reasonable magnitudes.

As for the control variables, our findings are consistent with the previous studies in literature. Older students tend to have a higher drop-out rate; one year increase in average age leads a 1.3% higher drop-out rate on average. Female students are 1.2% less likely to drop out compared to male students. Having a wealthier family reduces the probability of a drop-out; students coming from medium and high income families have 5% higher probability to continue their degree programs. Moreover, we see that all the information on secondary school education is relevant to the outcomes of students' tertiary education. Students graduated from high-school with a one point higher final score on average are 0.3% less likely to drop out. Also, the type of high-school has an effect on the academic outcomes. Students attended science lyceum programs in their secondary-schools perform better in their tertiary degrees compared to the students who have graduated from other types of high-schools. The same result goes for the areas of high-schools; students completed their secondary education in the North-west of Italy, where the corresponding university is located, seem to be more persistent in college. When a student moves in a new city, she might have some orientation problems and might struggle to get used to her new life. Especially considering the fact that Italians are known as having strong family bonds, suffering from homesickness might affect the drop-out decision of students. On the other hand, we observe that student-teacher ratio has only effect on the average credits but not on the drop-out rates which is not surprising considering the previous studies that concluded the same result (Carrieri et al. 2015, Betts and Morell 1999). According to our findings, nevertheless, having class size effect controlled by the student-teacher ratio has an influence on our treatment effect estimations so in any case we rather keep this variable in our analysis.

4.2 Changes in Students' Secondary School Backgrounds

Table 5 reports the results of the model explained in section 3.2 for the effects of the introduction of new selection procedure on high-school graduation marks. We see an increase of 2.5 points on average in graduation marks during the treatment years. Meaning that through the new selection procedure Economics receives students who have graduated from high-school with higher grades on average. This supports our main findings obtained from the baseline model. First, the improvement in observable characteristics of students is what one would expect after the implementation of the admission test given that performance of students during the last two years of high-school is part of the selection procedure. Secondly, we demonstrated in our previous results that there is a positive correlation between the student's high-school graduation mark and her tertiary education outcomes so that by showing the increase in high-school graduation marks we happen to provide an empirical evidence which explains the improvements in educational outcomes after the reform.

Table 6 presents the logit regression results of our DID set-up on graduated high-school types. Our findings suggest that the probability of having a student who graduated from vocational type of high-school is about 50% less on average after the introduction of admission test while the base outcome is the *liceo* type high-schools. Previously we shown that students graduated from vocational type of high-schools perform worse in their tertiary education, so that this significant reduction in the probability of receiving students graduated from those high-schools is another result that supports our main findings about the improvement of students' academic performances after the policy change.

4.3 Results of Placebo DID Designs

In order to show whether our main findings in Equation 1 are robust and the common trends assumption of diff-in-diffs approach is valid, we now present several results from our placebo difference-in-differences set-ups by using the pre-reform academic years from 2006/07 to 2011/12. Table 7 highlights the placebo treatment effects estimations obtained from three different equations, and each one of those equations consists of different samples. The first sample contains the academic years from 2008/09 to 2011/12 and we estimate placebo treatment effects for the years 2010/11 and 2011/12; as a result, we do not observe any significant effects for none of which placebo treatments. This means that the similar trend assumption is more likely to hold and our real treatment effects estimates are not outcomes of an ongoing trend which initiated before the treatment. Especially the drop-out rate of

Economics Department in 2011/12 academic year seems on the decrease compared to the previous years (Figure 1), however, according to our placebo estimations, that fall in 2011/12 does not have any statistical importance and might be an act of a general trend occurred across all departments. A resembling result is seen in the third sample which covers the academic years from 2006/07 to 2009/10 and none of the placebo treatments are statistically significant either. On the other hand, we observe two statistically significant placebo treatment effects in the second sample for the drop-out rates, yet these two coefficients are in the opposite direction of our real treatment effects so we still do not have any reason to doubt on the robustness of our main findings.

Table 8 reports the coefficient estimates of placebo and real treatment effects obtained from Equation 2 by using the academic years from 2006/07 to 2013/14. Given the academic year 2006/07 as benchmark, we see only one statistically significant effect which is on drop-out rates in the second treatment year 2013/14. This result suggests that during the pre-treatment years the trends of outcome variables follow similar patterns for treatment and control groups, and since the only significant change occurs after the reform we consider that this change is rather caused by the treatment's itself than a violation of common trend assumption.

4.4 Treatment Effects on Low Ability Students

We report the results of our extended DID set-up for the low-ability students, Equation 3, in Table 4. DID estimators for drop-rates of low-ability students are notably bigger in magnitude than our general treatment effects in Table 3; we observe, on average, a reduction of about 5% in drop-out rates for low-ability students after the reform. As for the average credits, low-ability students who exposed to treatment take 2.5 points more credits on average which is slightly smaller than our general treatment effects on average credits.

There are two main reasons can explain that why the selective admission test is more beneficial for the low-ability students in terms of the drop-out decision. First, students who passed the selection test might be self-motivated because these students are officially informed by the corresponding institute that they are good enough to be enrolled in relevant department and this might have led them to perform better and be more persistence in their degree programs. Second, since we have empirically shown earlier in this paper that after the reform treated department starts admitting more high-ability students on average, low-ability students find themselves in an environment that gives them an opportunity to interact with better peers so that they perform better in the end. Although distinguishing these two effects from one another is rather problematic due to the endogeneity and reflection issues in social interaction studies, our heterogeneous treatment effects estimations provide an evidence on a potential peer effect.

4.5 The Effects of Selection Procedure's Determinants On Drop-out Rates

We now present a bunch of OLS regression results on drop-out rates by using the information our data contains about the test-scores of students admitted to Economics department in the second year of treatment 2013/14.

Each column of Table 9 represents different regression result[3]. In the first column we see a significant effect of total test-score (60% test-score and 40% high-school score) of students on drop-out rate. One unit increase in the standard deviation of total test-score reduces drop-out probability about 2.3%. However, when we look seperately at the effects of two components (test-score and high-school score), it is clear that the entire effect is coming from the test rather than high-school score (columns 2 and 5). Even more, the effect of the test is driven by the mathematic section. One unit increase in the standard deviation of mathematic scores leads a reduction of 2.6% in drop-out rates (column 7). We do not observe any significant effect that coming from the other sections on drop-out rates. One interesting result is not to see any

[3]Each regression also includes several control variables, however, since our focus is only on the effects of the selection procedure's components, the parameter estimates of control variables are not presented in Table 9. The list of control variables, nevertheless, are available in Table 9.

significant effect from high-school scores of students. Even when the test-score is excluded from the right hand side of the equation, the estimated coefficient of high-school score is statistically insignificant. On the other hand, students' high-school graduation marks have a minor but statistically significant effect on drop-out rates (column 4), though we see that the effect disappears once the test-score is included into the equation. Nevertheless, based on the later situation it might be considered that high-school graduation marks could have been taken into account as well by the administrative office during the selection process, or even could have been a better substitute for the high-school scores.

5 Conclusions

In this paper, we have estimated the causal effects of selective admission test on drop-out rates and average credits of first year students by using a unique administrative data from a leading private university in Italy, where the Economics Department has started performing this new ex-ante selection procedure. We employed a difference-in-differences approach and found that the introduction of the new selection procedure plays a significant role on improving the academic outcomes of first year students by reducing the drop-out rate and increasing the average credits. We also provided some insights for the working mechanism of the selection test by showing that after the test high-school graduation marks and the probability of receiving a student who graduated from *liceo* type high-school are enhanced, so our empirical results met with our theoretical expectations. As a complementary to our main findings, we estimated the heterogeneous effects of the selective test on low-ability students and the results indicated that the low-ability students benefit more from the new policy. We attributed the latter result to a potential peer effect, nevertheless, it is also linked to the fact that self-selected students perform better regardless their performance in high-school once they pass a selection procedure. One possible future research topic, therefore, might be to pin down the peer effect in order to distinguish these two factors from each other. Finally, we have seen that the effects of the new selection procedure is coming from the test scores -more specifically from the mathematic scores- rather than the high-school scores of students.

Overall, the discussion on the necessity of a restrict access on tertiary education institutes is not only a local issue of the departments of corresponding university took part in this study, is also a nation-wide subject since the Italian education system has been experiencing high college drop-out rates for several decades. The present study, hence, has shed some light on an ongoing debate among students, universities and high administrative officials, and has shown that such restrictive policies can be a partial solution to deal with the high college drop-out rates.

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Appendix

Table 2: **OLS estimations of DID set up without controls**

	(1)	(2)
	Drop-out	Credits
Treatment Effects		
δ_1	-0.031**	5.802***
	(0.014)	(1.375)
δ_2	-0.038**	4.468**
	(0.015)	(1.845)
Treated Department		
Economics	-0.019*	-1.943**
	(0.010)	(0.957)
Treatment Years		
2012/13	0.0003	-0.225
	(0.008)	(1.158)
2013/14	0.005	0.679
	(0.008)	(1.525)
Constant	0.116***	40.882***
	(0.005)	(0.787)
N	19903	18416

robust and clustered standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: **OLS estimations of DID set up with controls**

	(1)	(2)
	Drop-out	Credits
Treatment Effects		
δ_1	-0.012	2.927
	(0.012)	(1.838)
δ_2	-0.033**	4.427*
	(0.014)	(2.259)
Treated Department		
Economics	-0.029***	-0.380
	(0.009)	(1.329)
Treatment Years		
2012/13	-0.004	1.124
	(0.009)	(1.659)
2013/14	-0.005	4.361
	(0.019)	(2.652)
Individual Characteristics		
Age	0.013***	-0.366***
	(0.001)	(0.089)
Female	-0.012**	-0.757
	(0.005)	(0.552)
Type of Highschools-Reference: Science		
Professional	0.115***	-7.692***
	(0.021)	(1.265)
Techinical	0.054***	-4.829***
	(0.007)	(0.531)
Classic	0.005	-2.076***
	(0.005)	(0.524)
Linguistic	0.026**	-4.773***
	(0.010)	(0.865)
Others	0.023***	-4.554***
	(0.006)	(0.502)
Family Income- Reference: Low		
Medium	-0.051**	0.208
	(0.023)	(1.225)
High	-0.049**	2.629**
	(0.024)	(1.158)
Areas of Highschools-Reference: North-West		
Central	0.035***	-3.171***
	(0.011)	(0.657)
Islands	0.060***	-6.849***
	(0.011)	(0.531)
North-East	0.032***	-2.028***
	(0.010)	(0.543)

Continued on next page

Table 3 – continued from previous page

	(1) Drop-out	(2) Credits
South	0.047***	-7.249***
	(0.009)	(0.561)
Others		
High-school F. M.	-0.0034***	0.497***
	(0.0002)	(0.028)
Student/Teacher	0.001	-0.561*
	(0.001)	(0.327)
Constant	0.359***	8.123***
	(0.033)	(2.904)
N	18858	17387

robust and clustered standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: **OLS estimations of heterogeneous treatment effects with controls**

	(1) Drop-out	(2) Credits
Heterogeneous Treatment Effects		
δ_{1L}	-0.046**	2.586*
	(0.020)	(1.487)
δ_{2L}	-0.061**	2.305
	(0.026)	(2.015)
Treatment Effects		
δ_1	0.004	1.853
	(0.014)	(1.751)
δ_2	-0.013	3.526
	(0.017)	(2.172)
Treated Department		
Economics	-0.032***	0.648
	(0.010)	(1.246)
Economics $\times$*Low*	0.004	-2.885***
	(0.011)	(0.892)
Treatment Years		
2012/13	-0.010	1.723
	(0.009)	(1.586)
2013/14	-0.011	4.496*
	(0.019)	(2.620)
2012/13 $\times$*Low*	0.013	-1.743
	(0.014)	(1.094)
2013/14 $\times$*Low*	0.011	-0.518
	(0.015)	(1.829)
Individual Characteristics		
Age	0.013***	-0.365***
	(0.001)	(0.088)
Female	-0.013**	-0.816
	(0.005)	(0.547)
Type of Highschools-Reference: Science		
Professional	0.114***	-7.740***
	(0.021)	(1.261)
Techinical	0.053***	-4.875***
	(0.007)	(0.521)
Classic	0.006	-2.074***
	(0.005)	(0.526)
Linguistic	0.026**	-4.778***
	(0.010)	(0.870)
Others	0.023***	-4.565***
	(0.006)	(0.505)
Family Income- Reference: Low		

Continued on next page

Table 4 – continued from previous page

	(1)	(2)
	Drop-out	Credits
Medium	-0.050**	0.211
	(0.023)	(1.218)
High	-0.047**	2.651**
	(0.024)	(1.151)
Areas of Highschools-Reference: North-West		
Central	0.035***	-3.114***
	(0.011)	(0.661)
Islands	0.059***	-6.8474***
	(0.011)	(0.529)
North-East	0.031***	-2.025***
	(0.010)	(0.542)
South	0.047***	-7.244***
	(0.009)	(0.559)
Others		
High-school F. M.	-0.0034***	0.465***
	(0.0002)	(0.032)
Student/Teacher	0.001	-0.556*
	(0.001)	(0.326)
Constant	0.356***	8.123***
	(0.032)	(2.904)
N	18858	17387

robust and clustered standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: **OLS estimations of DID set-up on high-school final marks with controls**

	(1)
	High-sch. F. M.
Treatment Effects	
δ_1	3.042***
	(1.079)
δ_2	1.958
	(1.227)
Treated Department	
Economics	-1.068
	(0.655)
Treatment Years	
2012/13	-1.035
	(0.985)
2013/14	-0.060
	(1.126)
Individual Characteristics	
Age	-0.399***
	(0.070)
Female	4.492***
	(0.378)
Type of Highschools-Reference: Science	
Professional	0.199
	(0.601)
Techinical	0.911**
	(0.359)
Classic	1.637***
	(0.347)
Linguistic	0.348
	(0.554)
Others	-0.142
	(0.264)
Areas of Highschools-Reference: North-West	
Central	2.660***
	(0.476)
Islands	7.226***
	(0.593)
North-East	1.997***
	(0.310)
South	5.859***
	(0.348)
Constant	73.043***
	(0.032)
N	19846

robust and clustered standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6: **Logit model estimations of DID set-up on high-school types with controls**

	(1)
	Vocational High-schools
Treatment Effects	
δ_1	-0.503**
	(0.236)
δ_2	-0.515**
	(0.255)
Treated Department	
Economics	0.229
	(0.149)
Treatment Years	
2012/13	0.202
	(0.185)
2013/14	0.209
	(1.181)
Individual Characteristics	
Age	0.096***
	(0.015)
Female	-0.375***
	(0.0674)
Areas of Highschools-Reference: North-West	
Central	-0.376***
	(0.091)
Islands	-1.389***
	(0.126)
North-East	-0.874***
	(0.095)
South	-1.145***
	(0.110)
Constant	-1.421***
	(0.297)
N	19846

robust and clustered standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7: **OLS estimations of placebo treatment effects with controls**

	(1) Drop-out	(2) Credits
Sample: 2008/09-2011/12		
$\delta_{2010/11}$	0.014	-1.648
	(0.015)	(1.831)
$\delta_{2011/12}$	-0.009	-0.960
	(0.011)	(1.645)
Sample: 2007/08-2010/11		
$\delta_{2009/10}$	0.036**	-1.970
	(0.014)	(1.933)
$\delta_{2010/11}$	0.029**	-2.351
	(0.013)	(1.817)
Sample: 2006/07-2009/10		
$\delta_{2008/09}$	0.021	0.296
	(0.013)	(1.1240)
$\delta_{2009/10}$	0.022	-2.340
	(0.016)	(2.078)

robust and clustered standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8: **OLS estimations of full sample placebo treatment effects with controls**

	(1) Drop-out	(2) Credits
Sample: 2006/07-2013/14		
$\delta_{2013/14}$	-0.037**	1.482
	(0.019)	(2.231)
$\delta_{2012/13}$	-0.015	0.148
	(0.017)	(1.730)
$\delta_{2011/12}$	-0.015	-2.596
	(0.017)	(1.834)
$\delta_{2010/11}$	0.008	-3.252
	(0.019)	(1.997)
$\delta_{2009/10}$	0.015	-2.898
	(0.019)	(2.030)
$\delta_{2008/09}$	-0.028	-0.291
	(0.017)	(1.508)
$\delta_{2007/08}$	-0.013	-1.432
	(0.018)	(1.593)
N	39263	36021

robust and clustered standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 9: **Estimates of the determinants of selection procedure on drop-out rates**

	1	2	3	4	5	6	7	8
	Drop-out	Drop-out	Drop-out	Drop-out	Drop-out	Drop-out	Drop-out	Drop-out
Total test-score	-0.023***	-	-	-	-	-	-	-
	(0.006)	-	-	-	-	-	-	-
Test-score	-	-0.023***	-	-	-0.023***	-0.022***	-	-
	-	(0.006)	-	-	(0.006)	(0.006)		
High-school score	-	-	-0.007	-	-0.005	-	-0.005	-
	-	-	(0.006)	-	(0.006)	-	(0.006)	-
High-school grad. mark	-	-	-	-0.011*	-	-0.006	-	-0.006
	-	-	-	(0.006)	-	(0.006)	-	(0.006)
Matematic-score	-	-	-	-	-	-	-0.026***	-0.025***
	-	-	-	-	-	-	(0.006)	(0.006)
Logic-score	-	-	-	-	-	-	-0.007	-0.007
	-	-	-	-	-	-	(0.006)	(0.006)
Culture-score	-	-	-	-	-	-	-0.002	-0.002
	-	-	-	-	-	-	(0.006)	(0.006)
English-score	-	-	-	-	-	-	-0.003	-0.003
	-	-	-	-	-	-	(0.006)	(0.006)
Number of Obsevartions	1489	1489	1489	1489	1489	1489	1489	1489

standard errors in parentheses, *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

the list of control variables used in each regressions: age, gender, type and area of high-school, family income.