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The effect of Extracurricular Activities on Students' Dropout. Evidence from Vocational Education in Italy

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Abstract

We study the effect of participating in extracurricular activities on the probability of dropping out of high school. The relationship between extracurricular engagement and dropout has been widely investigated by the sociological literature from a theoretical point of view. Students who are more involved in school life, and who are more integrated and committed, are expected to have a lower likelihood of dropping out. We test this hypothesis using administrative data on the population of students in vocational high schools in an Italian town. We employ a propensity score matching approach and find that participating in extracurricular activities reduces the probability of dropping out.

JEL Classification: I20, I21, I28.
Keywords: High school dropout; Extracurricular Activities; Student Engagement; Propensity score matching.

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1 Introduction

Dropping out of education is an issue of concern that affects more than 20% of secondary school students in most OECD countries (OECD, 2012). Governments across Europe are well aware of the importance of reducing the dropout rate and, indeed, the EUROPE2020 Agenda has renewed the Lisbon Strategy's commitment to reduce early school leavers to a maximum of 10% by 2020. Dropout is costly at both the individual and social level. Students who drop out are more likely to experience poor labour market outcomes, such as lower lifetime earnings and higher probability of unemployment, compared with students who progress with their studies (De Witte et al., 2013). Furthermore, dropouts are more likely to be poor, to be involved in criminal activities and to suffer poor physical and mental health in adulthood (Oreopoulos, 2006; Lochner and Moretti, 2004; Silles, 2009). In terms of the social costs of dropout, two effects can be identified. First, for each dropout there is a loss for the taxpayer since the cost of education provision cannot be recovered (e.g. staff salaries). Second, there is an increase in public spending to tackle the consequences of dropout, for example, higher unemployment and inequality.

There are several possible determinants of high school dropout (Rumberger, 2011). A large body of the empirical economics literature highlights the role of personal (e.g. gender, ethnicity and personality traits) and family characteristics (e.g. parental education, single parenthood and family income), as well as time preferences, student-course mismatch, automaticity, and foregone health care (Bratti, 2007; Ermish and Francesconi, 2001; Mocetti, 2008; Oreopoulos, 2007; Stinebrickner and Stinebrickner, 2012, 2014; Goux et al., 2017; Heller et al., 2017; Migali and Zucchelli, 2017). The main findings suggest that those individuals at higher risk of dropout are males, Hispanics or blacks, have low academic or cognitive abilities, and are from disadvantaged backgrounds or have parents with lower levels of education. Students with low levels of conscientiousness and high levels of neuroticism, and students who forgo health care, are also at a higher risk of dropping out. These studies focus on the effects of observable socio-demographic characteristics, cognitive skills and non-cognitive abilities. From a theoretical point of view, in the economics literature, dropout decisions are traditionally explained by either the human capital model or by the signalling model (Bedard, 2001). According to the first model, an individual accumulates human capital through education and decides to drop out when the costs attached to achieving a higher degree of human capital are higher than the expected benefits. In this framework, any level of education augments the set of skills and abilities that are valued in the labour market. Thus, even for dropouts there is a (small) increment in their human capital endowment. On the contrary, signalling theory suggests that what matters is the actual achievement of a qualification, which is then used to infer an individual's ability in the labour market. Thus, dropouts will always be perceived as low ability and less productive by employers. More recently, Stinebrickner and Stinebrickner (2012, 2014) describe a

third theoretical approach by which the dropout decision is the fruit of a process of expectations revision. Following this line of thought, when a student enrols to a certain high school or university he/she does not know whether their ability level is suited to that programme of study. Therefore the student decides to drop out as a consequence of a process of revision of expectations.
The sociological literature has largely contributed to the dropout discussion by developing an alternative theoretical approach. The student integration model of Tinto (1975), which stems from Durkheim's theory of suicide, compares the decision to drop out with the decision to commit suicide. Dropout is seen as consequence of a lack of integration and commitment between the student and the school. An important feature of Tinto's model is the implication that participating in extracurricular activities may reduce dropout behaviour. If the school provides not only curricular activities but also cultural and social activities, counselling, and opportunities to participate in sport or work training, then students feel part of a community and are less likely to drop out. Finn (1993) developed an alternative theory where student engagement is the key determinant of dropout decisions. Consequently, participation in extracurricular activities may increase student involvement in school life and reduce the probability of dropout. McNeal (1995) combining the social control theory and Finn's theory, empirically evaluates whether extracurricular activities can be considered as a proxy for student integration. He finds that participation in activities such as athletics and fine arts reduces significantly the probability of dropping out from high school. Our work has the advantage of trying to model the selection into treatment by employing propensity score matching.

The effect of extracurricular activities on dropout has been largely under-investigated by the empirical economics literature, and our work aims to fill this gap. Contextually, we attempt to test the sociological hypothesis that participation in extracurricular activities increases student engagement and hence reduces the risk of dropout. Furthermore, there are limited school and governments investments in extracurricular activities. Hence, a better understanding of the relationship between participation in extracurricular activities and dropout also has important policy implications for investment in such activities. We estimate the effect of participating in extracurricular activities (comprising cultural, pedagogic, career counselling and sport activities) organised by the high school on the probability of dropping out. We employ unique administrative data that include the whole student population of vocational high schools in a town of the Italian province of Catanzaro,[1] observed for three years from 2008-09 to 2010-11. We adopt a propensity score matching methodology, and we find that in 2008-09 and 2009-10 participating in extracurricular activities strongly decreases high school dropout by by between 4 and 4.3% and 6.9 and 7.5%, respectively, depending on the matching algorithm used. In 2010-11 the effect is still negative though not statistically significant.

[1]For confidentiality reasons the name of the town is undisclosed in order to avoid the identification of the schools.

2 Institutional context

The Italian secondary school system is a three tier system where students can enrol into a *Liceo*, a Professional or a Technical high school. The *Liceo* aims at preparing students to access university. Within this academic track students can specialise in different fields (e.g. Humanities, Science, Art).

The Technical and Professional tracks are both vocationally oriented, even though the first provides a mix of theoretical and highly specialised technical knowledge while the professional track equips students with practical knowledge. The technical high schools can be either economic or technological, and within these subdivisions there are different specialisations such as marketing and finance, IT, tourism, electronics and electrical engineering, and agriculture. The Professional high schools also provide a variety of programmes, such as engineering, agriculture, catering.

All programmes last five years and after passing a final exam students receive a diploma or secondary school qualification. However, every year students are required to pass a certain number of courses whose content is mainly decided at national level (around 85% of the curricula for each programme is defined by the Ministry of Education). The grading system ranges from 0 to 10 with 10 being the highest mark and 0 the lowest. The requirement to be admitted to the next school year is to obtain at least a 6 in all modules. However, if a student obtains a slightly lower mark in one or two modules, the teaching committee can decide to pass her, conditional on attendance at a catch-up course. Students who fail have to re-enrol in the same year (grade).

Schools can organise extracurricular activities. Most of the activities are funded by the European Structural Funds (PON 2007-2013)[2], one of the objectives of which is the funding of activities that can help reduce the risk of dropping out (Objective F)[3]. The idea is that participation in these extracurricular activities may improve individual self-perception, self-esteem and confidence and hence reduce the risk of dropout. . Schools can implement activities that are targeted at all students, and in many cases, the whole class is involved in a particular activity. However, in some cases, the school could design projects for specific students from different classes. In very rare cases, participation in such activities is on a voluntary basis. There is no penalty for not participating. Although we do not know the exact cost of each project organised within the school, we do know that in the period 2007-2013 the European Structural Funds provided a total of 252,102,686 euros to fund school's extracurricular activities to reduce dropout in the four Italian convergence regions (i.e. Calabria, Campania, Puglia and Sicily). Given a student enrolment of 511,568, this implies

[2] *PON-Piano Operativo Nazionale "Ambienti per l'apprendimento" FESR*

[3] In particular, to achieve this objective there has been an investment of 270 millions euros with 5700 projects funded and 450,000 participants in the so-called "4 Convergence Regions".

a cost per student of 492.8 euros.[4] As to be expected, there is considerable variability in the costs per student depending on the nature of the project.

3 Data

We use administrative data provided by the local education authority of a medium size town in the Province of Catanzaro in Italy. The data cover the student population enrolled in the three vocational high schools in the town, covering a total of about 1400 students per year observed from 2007-8 to 2011-12. For each school year, we can observe all students enrolled from grades 1 to 5. Therefore, most students we be aged between 14 to 19 years. We have information on individual characteristics (gender, age, nationality, disabilities), student performance (annual marks, area of specialism) and school characteristics (class size, peer effects in the previous year, and school budget). We also observe whether students participate in extracurricular activities organised within the school[5]. Unfortunately, given the administrative nature of the data it is not possible to know whether the students are taking part in similar activities in their free time.

The binary variable dropout is our dependent variable. It takes a value of one if a student has formally withdrawn from school during a given year, or if she did not enrol for the following year. In order to generate this variable we have to exclude the school year 2011- 12 from our final sample. A further restriction is that our sample is confined to students enrolled in grades 2 to 5, we have to exclude grade 1 to be able to generate the variables for prior attainment and peer effect. We do not consider students enrolled in evening courses since they differ from other students in terms of age, working conditions and marital status. We also exclude all students transferring to courses not present in our dataset.

Table 1 reports summary statistics for each variable, for all students in our analysis sample as well as separately for continuers and dropouts, for each of the three years included in our analysis. The participation rate in extracurricular activities ranges between 20% and 27% depending on the school year analysed. In all years the percentage participating in extracurricular activities is much higher among continuers than among dropouts[6]. However, in 2010-11 the gap between continuers and dropouts is much smaller than in the two previous years[7].

[4]Data are obtained from the evaluation report "Servizio di valutazione indipendente del Programma Operativo Nazionale "Competenze per lo sviluppo" 2007-2013 - Obiettivo Convergenza".

[5]The activities can be cultural, pedagogic, career counselling or sport ones.

[6]For 2008-09, 28.2% of continuers take part in extracurricular activities while only 9.6% of dropouts do the same. For 2009-10, those shares are 27.3% and 6.9%, respectively.

[7]Among continuers 21.3% do take part in extracurricular activities, whilst among the dropout group 14.8% of the students participate.

Around 43% of the students are female and 57% are male; these proportions are stable over the period of our analysis. The higher share of male students is explained by the vocational nature of the high schools analysed. In fact, some of the study programmes are characterised by a certain degree of gender stereotyping. The proportion of males is higher among dropouts than among continuers, for all three years. In particular, in 2008-09 we observe that 82.6% of dropouts are male. Students are, on average, 16.43 years old, with dropouts being slightly older than continuers. This can be explained by the fact that among dropouts there are more students who fail and who have been required to repeat the same year. The share of disabled students is between 1.6% and 2% depending on the year. The descriptive statistics do not suggest a particularly strong relationship between disability and dropout. The data suggests that on average dropouts are less likely to be foreigners than are continuers. This might be a result of self-selection, since the foreign students enrolled in high school may on average be the more committed and able pupils.

An important variable for our analysis is the average mark obtained by each student in the previous year[8]. In order to construct this variable we have to exclude the school year 2007-08 from the analysis. This variable can be used as an imperfect proxy for student ability, indeed according to the human capital theory education generates a continuous accumulation of knowledge and skills. Moreover, educational outcomes are the composite result of various inputs in the educational production function. Hence, by using the previous average mark obtained we indirectly take into account a series of unobservable inputs (such as family, educational and social characteristics) that influence student achievement. Furthermore, we disaggregate the average mark into several mutually exclusive dummies from the lowest to the highest mark[9]. More specifically, "Average Mark Previous Year: 4-5.99", for instance, is equal to one for those students who obtained an average mark in this range and did not fail, and zero otherwise. The proportion of students who failed the previous year ranges between 3.8 and 6.6 per cent. Not surprisingly, there is a much higher percentage of students who fail among dropouts than among continuers. Conversely, there are more students with good (7-7.99), or excellent (8-10) prior average marks among the continuers than there are among dropouts.

In 2008-09 and 2009-10, a higher share of students who drop out are in the first two grades (2 year Foundation) compared with continuers. However, this is not true for the last year where there is a slightly higher proportion among continuers. This means that there is a higher likelihood of

[8]This variable is constructed by averaging the marks obtained in all modules by each student.

[9]We have disaggregated this variable into mutually exclusive dummies in order to take into account possible non-linearities. Moreover, this technique allows us to distinguish between students with an average mark lower than the pass grade but that did not fail, and students with a mark lower than the pass mark who did indeed fail.

dropping out in the first 2 years of study than in the remaining ones and that the last year is the one with a lower likelihood of withdrawing. In terms of area of study, we note that it is only for IT and Tourism that there is a consistent pattern for all three years. In particular, we observe that it is more common for continuing students to be enrolled in these courses than for dropouts.

We also construct a variable that aims to capture peer effects, "peer effects previous year", based on the average mark of former classmates in the previous school year. We see that for the first two years, the average mark among former classmates is higher among continuers than dropouts. However, this is not the case for 2010-11 where we the average mark among former classmates is slightly higher for dropouts[10].
The average class size is around 20 students in all years, with little difference between dropouts and continuers. Above we reported that the percentage of students participating in extracurricular activities ranged between 20% and 27% across the three years of our analysis period. Table 2 shows the percentage of students taking part in extracurricular activities by school year (grade), pooled across the three years of our sample. Participation rates are lower in the final 2 school years (grades 4 and 5), but students in all grades are participating in these activities.

We do not report the participation rate by grade for the three schools separately, however it is worth noting that in one school there are no students taking part in extracurricular activities in their final grade (year 5). However, this appears to be the result of a specific school policy rather than the result of decisions made by individual pupils. Indeed, the dropout rate in the final year for that particular school is relatively low compared to the other years.

The last 3 columns of Table 2 show that the percentage of students who drop out is higher in grades 2-4 than in the final year, grade 5. This is in line with the idea that by the time students have reached the fifth year, they have invested considerable time and effort in order to do so and are therefore motivated to finish High School with a qualification. This is not surprising given the well-documented sheepskin effect.shows that the share of dropouts is higher in grades 2-4 than in the final year. This is in line with the idea that fifth year students have invested more time and put in more effort to reach the final year, therefore, they are motivated to finish High School with a qualification. This is not surprising given the well known sheepskin effect (Jaeger and Page, 1996).

[10]These differences are very small and likely not significant.

4 Methodology

We first estimate a series of discrete choice models to evaluate whether participating in extracurricular activities, together with other established determinants, has a significant effect on the probability of dropping out. However, these models allow the estimation of simple correlations and may suffer from omitted variable bias. Therefore, our main empirical strategy is based on non-parametric single treatment propensity score matching methods. The latter do not impose functional form assumptions and produce more robust estimates based on samples of treated and control groups which are similar in terms of their observable characteristics.

Discrete choice models

We estimate the following probit regression models

$$P(y_i = 1|X_i) = \Phi(\alpha + \beta X_i + \gamma ECA_i) \tag{1}$$

where $i = 1 \ldots N$ are high school students; y_i is our dependent variable, which takes a value of 1 if individual i is a dropout, and zero otherwise. ECA_i is our parameter of interest, a dummy variable for participating in extracurricular activities organised by the school. X_i is a vector of individual and and school characteristics. More specifically, we control for gender, age, nationality and whether the student has a physical or mental disability. We also include the average mark obtained by each student in the previous year. This variable is disaggregated into five categories from the lowest to the highest mark, by doing so we aim to capture some of the effects of student ability which may have a non-linear relationship with the likelihood of drop-out. We also control for area of specialism by including a dummy for each programme area. Furthermore, we control for peer effects by including our variable capturing the average mark of the studentÕs classmates in the previous year. Finally, we control for class size and per-capita school budget. The standard errors are clustered at class level, to take account of the possible heterogeneity between students assigned to different classes.

Matching models

Propensity score matching is based on the identification of two groups: pupils who are not participating in any extracurricular activities (the control group) and pupils who are actually participating in those activities (treated group). The requirement is that untreated pupils should be similar to the treated ones in all relevant pre-treatment observable characteristics, except for participation in extracurricular activities. Matching methods rely on two fundamental assumptions: (i) *common support*, i.e. pupils with the same pre-treatment characteristics have a positive probability of taking part in extracurricular activities; and (ii) *conditional independence assumption* (CIA), i.e. selection into treatment is based solely on observable characteristics. The latter means that there must not be any unobservable characteristic that affects both the probability of receiving treatment and the potential outcomes. If this is true, the mean difference in outcomes, weighted by the propensity score distribution for the observations on the common support, will provide an estimate of the average treatment effect. Equation 2 shows the Average Treatment Effect on the treated:

$$\tau_{ATT} = \sum_{i \in p} (Y_i - \sum_{j \in np} W_{ij} Y_j) \, w_i \tag{2}$$

where W_{ij} and w_i are, respectively, the weights assigned to pupils in the control group when they are matched with treated individuals, and the weights used to build the distribution of the outcome for the participants. The weights W_{ij} can take different forms depending on the matching estimator used. We employ four matching algorithms: nearest neighbour with replacement, caliper, radius and kernel matching. In the first case we provide analytical standard errors (Abadie and Imbens, 2008), for all others we present bootstrapped standard errors. When implementing the nearest neighbour method, we match a non-participant pupil to more than one participant (replacement option). This approach reduces bias and enhances the quality of the matching. However, the variance of the estimator increases because there are fewer distinct non-participants used (Smith and Todd, 2005).

Caliper matching imposes an upper bound on the maximum propensity score distance between treated and untreated pupils. This technique helps to avoid bad matches and increases the matching quality. A possible limitation is the a priori choice of the tolerance level. In our analysis we impose a very small caliper of 0.005, which implies that each matching partner is very close in terms of propensity score. We also employ a variant of caliper matching, radius matching. This algorithm consists of matching with all nearest neighbours within a certain caliper. Therefore, it has the advantage of reducing variance while avoiding bad matches. Finally, we estimate the effect using kernel matching. This estimator has the advantage of reducing the variance by employing almost all control observations. However, it has the disadvantage of an increased risk of finding bad matches. In practice, as discussed in Section 5, the choice of matching algorithm makes little substantive difference to our results.

4.1 Propensity Score Estimation and Quality of Matching

In Table 4 we present the results of estimating the probability of participation in extracurricular activities versus non-participation using probit regression. The model specification should include variables that simultaneously influence the participation decision and the dropout decision, and are also unaffected by participation itself. Therefore, we include time invariant individual characteristics such as gender and nationality, but also age and average mark in the previous year, which are pre-treatment variables. In order to identify a causal effect the model specified should satisfy the conditional independence assumption (Rubin and Thomas, 1996; Heckman et al., 1998). To verify whether the variables included in the propensity score are properly balanced across treated and control groups, and to assess the quality of the matching, we compute the Standardised Bias. This is a suitable indicator, proposed by Rosenbaum and Rubin (1985)), which evaluates the distance in the marginal distribution of the covariates. For each variable, we compare the standardised difference in means by participation status before and after matching.[11]. In most empirical applications a reduction of the bias below 5% is considered sufficient for good matching. Figures 1 to 3 plot the covariatesÕ standardised bias before and after adjustment. In any school year and for each covariate, we observe a significant reduction of the bias after adjustment, which is always close to zero. Therefore, we are confident that the covariates used in our propensity score are properly balanced.

The second important assessment to evaluate the quality of the matching is to verify the overlap and the region of common support. The common support assumption implies that both participant and non-participant students should have a positive probability of participating in extracurricular activities, as shown by the distribution of the propensity score.

We present two common methods to check this condition. The first is a comparison of the minima and maxima of the propensity score, the second method is the graphical visualisation of the density distribution in the treated and control groups.

Starting with the first test, in 2008-09 the distribution of the propensity score of the participants ranges in the interval [0.0721-0.6379], while the distribution for non-participants lies in the interval [0.0025-0.6270]. The region of common support is therefore [0.0721, 0.6270], which implies that we need to discard the observations outside this range. In 2009-10, the interval for participants is [0.0916-0.6674] and for non-participants is [0.0330-0.6111], thus the region of common support is [0.0916-0.6111]. Finally, in 2010-11 we have perfect overlap because the region of common support corresponds to the interval of the treated [0.0575-0.3738], whereas the interval for the untreated is [0.0364-0.3775].

Figures 4 to 6 6 show the propensity score distribution for the treated and control groups. The requirement is that for each treated student there exists a potential match in the control group. We expect to graphically observe that the distribution of the participants lies within the range of the

[11]

$$SB = 100\frac{(\bar{x}_{\text{non-participants}} - \bar{x}_{\text{participants}})}{\sqrt{0.5(s^2_{\text{non-participants}} - s^2_{\text{participants}})}}$$

where $\bar{x}_{\text{non-participants}}$ and $s^2_{\text{non-participants}}$ are the mean and the variance in the control group, and $\bar{x}_{\text{participants}}$ and $s^2_{\text{participants}}$ the analogue for the treated group.

distribution of the non-participants. The above mentioned figures for each school year, confirms the conclusion of the min-max test: we have to discard very few observations in the right-hand tail of the participants distribution for the years 2008-09 and 2009-10[12]. Overall the two methods show that the common support condition is largely met. However, we recognise that given the relatively small number of covariates in the propensity score specification, care has to be taken in assessing the sensitivity of the results to the existence of hidden bias.

5 Results

Probit models

Table 3 reports the results of the probit estimations for the three school years under investigation.[13] For each year we present two different specifications. In Model 1, we estimate the probability of dropping out as a function of participation in extracurricular activities, individual characteristics (gender, age, disability, foreign citizenship), attainment in the previous year and area of specialism. In Model 2, we additionally include peer effects from the previous year and school characteristics, although this results in a reduction in the sample size.

Focusing on our variable of interest[14], participating in extracurricular activities decreases the probability of dropout in all school years and in both models. The effect is always negative and statistically significant at the 1% level in 2008-09 and 2009-10, however, in 2010-11, the estimates are not significant. The effect ranges between 2 and 6 percentage points (pp). This corresponds to a 47% reduction in the dropout rate in 2008/09 and around a 70% reduction in 2009/10. There are no substantive differences between Models 1 and 2.

Looking at the other covariates, the effects observed are in line with those seen in the existing literature. Males have a higher probability of drop out compared with females, but the effect is only statistically significant in 2008-09, when it increases the probability of dropping out by around 4pp. Older students are more likely to drop out than younger students, this effect is significant across all years and models (with the exception of model 2 in 2008-09), with the magnitude of this effect ranging from a minimum of 2.5pp to a maximum of 4pp. Being disabled has a negative and statistically significant effect only in 2008-09, Model 1.

The estimates for foreign students are negative in all years, although not always significant. In general, it appears that being a foreigner reduces the probability of dropout between 3pp and

[12]The number of discarded observations ranges between 0 and 6 depending on the year and matching algorithm used.

[13]We have also estimated a pooled linear probability model with individual fixed effects and we have reported the results in Table B1 in the Appendix B. However, our preferred approach remains the cross-sectional probit analysis, which also allows the evaluation of the effect of time invariant covariates making our specifications less parsimonious.

[14]For simplicity and ease of interpretation we only report the marginal effects

5pp. Unfortunately, due to the small number of observations we cannot distinguish effects by nationality. Existing literature has suggested variation by ethnic group with, for example, higher rates of dropout among those of African origin and lower probability of dropout among Chinese and Asian students.

The results also indicate that students with higher previous average marks have a lower probability of dropout compared to those who fail. The effect, however, is not always statistically significant and varies across years and specification.

We recall that the area of specialism is chosen when students start their third grade, therefore the effect on dropout has to be interpreted in comparison to the first two grades. We notice that each area of specialism has a negative, although not always significant, effect on dropout compared to the 2 year foundation. However, the largest effect, which is consistently significant across models and years, is observed for information technology (reducing the probability of dropout by between 6pp and 8pp). Finally, the coefficient for peer effects is only statistically significant in 2009-10. The sign is positive and may suggest that students who feel the competitive pressure of their brighter peers are more likely to drop out. The effect of class size is positive and significant only in 2009-10, and is consistent with findings in existing studies that larger classes increase the probability of drop out. Finally, it is also worth noting that there is no effect of school per-capita budget on drop out, this may be due to the fact that we only have three schools in our sample and thus limited variation.

Matching models

Table 5 shows the results of the propensity score matching estimation. Before matching, the effect of participating in extracurricular activities is negative and statistically significant in all school years. The magnitude of this effect ranges from a minimum of a 4.1% reduction in the dropout rate in 2010-11 to a maximum of 9.4% in 2009-10. After matching, and for all algorithms used, the estimated effects in 2008-9 and 2009-10 are between 50% and 80% of the magnitude of the unmatched estimates. More precisely, in 2008-9, the ATT is statistically significant at the 1% level and corresponds to a decrease in dropout of around 4%, whereas in 2009-10 there is a reduction of around 7%. In 2010-11 the matched effect is still negative though not statistically significant. A possible cause is the smaller number of participants in this year, around 277 depending on the algorithm used. In the previous two school years, we observe a much larger number of participants, over 340 in 2009-10 and 375 in 2008-09. Furthermore, by restricting the matching analysis to observations for which there is common support, we lose very few pupils (at most 6 in 2009-10 with a caliper or radius algorithm). As discussed earlier in section 4, the identification of the average treatment effect on the treated is based on the assumption that there are no unobservable factors that influence both the probability of participation in extracurricular activities and the probability of dropping out of education. This is equivalent to the assumption of no hidden bias, which cannot be directly tested. However, to assess the robustness of our estimates we use a ‘pseudo’ confounding factor method, the *Rosenbaum Bounds*. Further details are provided in Appendix A.

This procedure addresses hidden bias in general, that is, it evaluates situations of both positive and negative selection into participation. In our analysis, our estimated effect is already a conservative effect with respect to positive selection - i.e students who have a higher probability of participating in extracurricular activities are also more likely to drop out. We are interested, instead, in negative selection - i.e. confounding factors that may increase participation and reduce dropout. Therefore, in Table 6, we report the bounds for negative selection and the corresponding significance levels.[15] We note that we would need to question the validity of our ATT for levels of hidden bias that increases the participation probability by more than 100% ($e^{\gamma} = 2$)[16]. Naturally, this is a worst case scenario. It means that the confidence interval for the effect of participating in extracurricular activities would include zero, if an unobserved factor caused the odds ratio of participation to differ between treatment and control groups by more than 2.[17]. We can conclude that, notwithstanding the low number of covariates in the propensity score specification, our results are reasonably robust to the existence of hidden bias. Therefore, we can reasonably state that the conditional independence assumption is satisfied.

6 Conclusions

In this paper we have investigated the effect of participating in extracurricular activities on the probability of drop out from high school. We do so using unique data obtained from vocational schools in a town in the south of Italy. Implementing both discrete choice models and propensity score matching our findings confirm the existence of a negative relationship between participating in extracurricular activities and dropout. Based on our matching estimates, we find a decrease in the dropout probability of around 4% to 7%, dependent on the year and model specification. Although we cannot claim that this is a causal effect, the strong correlation that we find is also robust to increasing levels of hidden bias. While the role of extracurricular activities forms a central part of sociological theories on dropout, it has been largely under-investigated by the empirical economics literature. Our contribution is therefore twofold, contributing to the economics literature on dropout and confirming the sociological hypothesis that student engagement is an important

[15]We only consider 2008-09 and 2009-10 because in 2010-11 the ATT is not statistically significant.

[16]We report in the table only the p-values for the bounds up to $e^{\gamma} = 2$. However, we have estimated the bounds up to $e^{\gamma} = 10$ and can confirm that our estimates are not sensitive to a level of hidden bias that would increase by ten times the participation probability.

[17]As noted earlier, we have estimated the sensitivity to a bias that would increase the treatment probability by 10 times and our estimates are still not driven to zero

determinant of dropout.

From a policy perspective, our analysis also contributes to the evaluation of some of the actions, financed by the European Structural Funds (PON 2007-2013), that aim to reduce rates of dropout. Moreover, our results suggest that funding extracurricular activities within schools is a promising approach for discouraging students from dropping out of the school system.

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A Rosenbaum Bounds

The idea is that the probability of participation is a function of both observable (x_i) and unobservable (u_i) factors, such that for individual i:

$$P_i = P(D_i = 1|x_i, u_i) = F(\beta x_i + \gamma u_i) \tag{3}$$

where D is the treatment dummy variable. If the CIA is valid and there is no hidden bias, the value of γ is zero.
Assuming that F is a logistic distribution and that the matching procedure gives us couples of treated and untreated individuals (i e j), we can write the odds ratio of being a participant as:

$$\frac{P_i(1 - P_j)}{P_j(1 - P_i)} = \frac{exp(\beta x_i + \gamma u_i)}{exp(\beta x_j + \gamma u_j)} \tag{4}$$

The matching procedure makes sure that $x_i = x_j$, thus we are left with $exp[\gamma(u_i - u_j)]$. The CIA entails that γ is zero such that either the effect of unobservable factors is zero or those factors are the same for both participants and non-participants ($u_i = u_j$).
Values of $e^\gamma > 1$ imply that there is hidden bias. In particular, a certain value of e^γ represents the effect that an unobservable factor should have on the probability of participation, in order to drive the ATT to zero.
Becker and Caliendo (2007) have written a Stata program that implements this sensitivity analysis through the test-statistic Mantel-Haenszel (Q_{MH}). Rosenbaum (2002) shows that for values of $\gamma > 1$, Q^+_{MH} represents the case when the average treatment effect is overestimated while Q^-_{MH} represents the case in which the effect is underestimated.
Table 6 shows only the Q^+_{MH} bounds, their level of significance for different values of e^γ and for different matching algorithms. A significant value implies that the result is insensitive to the corresponding level of hidden bias (Becker and Caliendo, 2007).

Figure 1: Covariates Balance - 2008-2009.

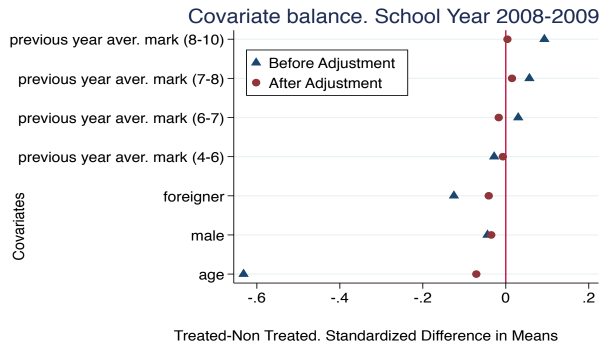

Figure 2: Covariates Balance - 2009-2010.

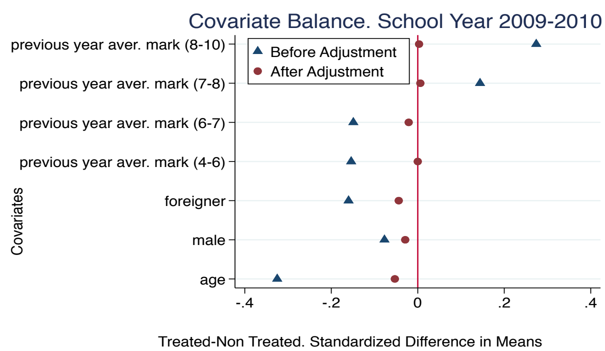

Figure 3: Covariates Balance - 2010-2011.

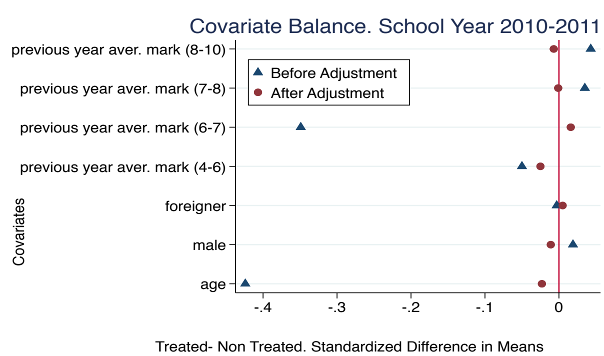

Figure 4: Distribution of the *Propensity Score* for treated and non-treated individuals, 2008-2009

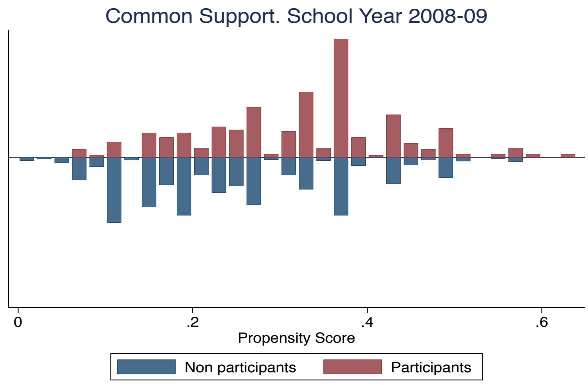

Figure 5: Distribution of the *Propensity Score* for treated and non-treated individuals, 2009-2010

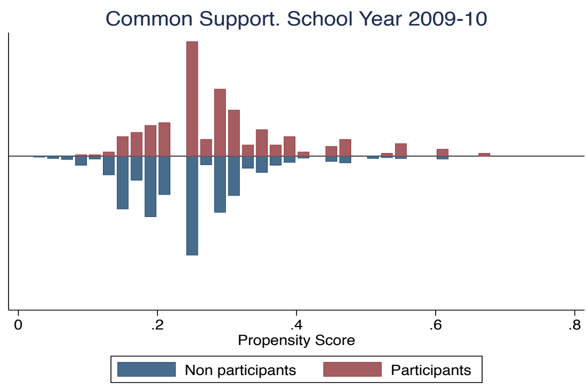

Figure 6: Distribution of the *Propensity Score* for treated and non-treated individuals, 2010-2011

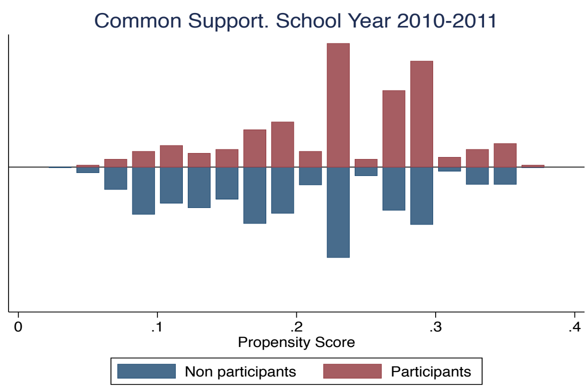

Table 1: Descriptive Statistics

	2008-09				2009-10				2010-11			
	All	*Continuers*	*Dropouts*	*N*	*All*	*Continuers*	*Dropouts*	*N*	*All*	*Continuers*	*Dropouts*	*N*
HS Dropout	8.13	0.00	100.00	1413	9.60	0.00	100.00	1365	11.03	0.00	100.00	1350
Participation to Extracurricular Activities	26.67	28.19	9.57	1410	25.35	27.31	6.92	1365	20.59	21.31	14.77	1350
Males	56.61	54.31	82.60	1413	57.25	55.59	72.52	1366	56.88	56.45	60.40	1350
Age	16.43	16.38	17.09	1413	16.37	16.32	16.74	1366	16.44	16.38	16.85	1350
Disable	1.98	2.00	1.74	1413	1.61	1.30	4.58	1365	1.63	1.75	0.68	1348
Foreigner	3.40	7.82	3.00	1413	3.81	3.81	3.82	1365	4.38	4.58	2.74	1347
Failed Previous year	6.58	6.24	10.43	1413	4.10	3.73	7.63	1366	3.78	2.91	10.74	1350
Average Mark Previous Year:4-5.99	0.99	1.00	0.87	1413	0.88	0.97	0.00	1366	1.11	0.75	4.03	1350
Average Mark Previous Year:6-6.99	30.29	31.74	13.91	1413	33.46	33.63	31.30	1366	20.67	20.73	20.13	1350
Average Mark Previous Year:7-7.99	10.12	10.71	3.48	1413	10.18	11.02	2.29	1366	8.22	8.66	4.70	1350
Average Mark Previous Year:8-10	5.38	5.86	0.00	1413	4.83	5.35	0.00	1366	3.33	3.41	2.68	1350
2 Years Foundation	12.88	12.40	18.26	1413	12.08	11.10	21.37	1366	10.81	10.82	10.74	1350
Accounting and Marketing	23.28	24.27	12.17	1413	23.21	24.64	9.92	1366	24.59	22.40	42.28	1350
Surveying	16.77	16.49	20.00	1413	16.25	16.53	12.98	1366	16.89	17.90	8.72	1350
Catering	20.52	18.49	43.48	1413	23.43	22.61	31.30	1366	24.74	25.40	19.46	1350
Electrical	2.83	2.93	1.74	1413	3.88	2.84	13.74	1366	4.15	3.91	6.04	1350
IT	10.62	11.48	0.87	1413	6.52	6.81	3.82	1366	2.74	3.00	0.67	1350
Tourism	13.09	13.94	3.48	1413	14.64	15.48	6.87	1366	16.07	16.57	12.08	1350
Peer effects previous year	6.47	6.48	6.23	951	6.60	6.61	6.48	955	6.44	6.43	6.49	920
Class size	19.67	19.64	19.99	1413	20.00	19.93	20.75	1366	20.59	20.60	20.58	1350

Table 2: Participation and Dropout by school year. All years (2008-09 to 2010-11)

School Year	*Non Participants*	*Participants*	*Total*	*Continuers*	*Dropouts*	*Total*
Grade 2	1,120	482	1,602	1,448	159	1,607
	69.91	30.09		90.11	9.89	
Grade 3	1,055	412	1,467	1,319	148	1,467
	71.92	28.08		89.91	10.09	
Grade 4	1,143	192	1,335	1,159	176	1,335
	85.62	14.38		86.82	13.18	
Grade 5	977	186	1,163	1,107	55	1,162
	84.01	15.99		95.27	4.73	
Total	4,295	1,272	5,567	5,033	538	5,571
	77.15	22.85		90.34	9.66	

Table 3: Determinants of Dropout - Marginal effects Probit analysis

	2008-09		*2009-10*		*2010-11*	
Dep. Var.	*Model 1*	*Model 2*	*Model 1*	*Model 2*	*Model 1*	*Model 2*
Extracurricular activities	-0.038**	-0.032*	-0.067***	-0.067***	-0.023	-0.034
	(0.015)	(0.018)	(0.013)	(0.013)	(0.020)	(0.022)
Individual Characteristics						
Male	0.044***	0.033**	0.010	0.016	0.024	0.029
	(0.013)	(0.013)	(0.016)	(0.012)	(0.023)	(0.023)
Age	0.017***	0.004	0.028***	0.025***	0.034***	0.042***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.012)
Disabled	-0.037***	0.013	0.067	0.059	-0.058	-0.031
	(0.013)	(0.044)	(0.070)	(0.058)	(0.037)	(0.054)
Foreigner	0.030	-0.025	-0.036*	-0.029***	-0.041	-0.049**
	(0.022)	(0.020)	(0.022)	(0.011)	(0.025)	(0.024)
Outcome previous year[2]						
Average mark previous year: 4-5.99	-0.037**	0.011			0.276***	0.280**
	(0.016)	(0.069)			(0.103)	(0.113)
Average mark previous year: 6-6.99	-0.054***	-0.021*	-0.032**	0.005	-0.021	-0.000
	(0.010)	(0.012)	(0.015)	(0.012)	(0.018)	(0.019)
Average mark previous year: 7-7.99	-0.032**	-0.017	-0.068***	-0.026	-0.050**	-0.025
	(0.014)	(0.017)	(0.017)	(0.018)	(0.022)	(0.028)
Average mark previous year: 8-10					-0.039	-0.012
					(0.029)	(0.033)
Study Programme[3]						
Accounting and marketing	-0.045***	-0.048	-0.081***	-0.050**	0.059	-0.038
	(0.014)	(0.039)	(0.012)	(0.022)	(0.045)	(0.088)
Surveying	-0.017	-0.067***	-0.050***	-0.058***	-0.065***	-0.090*
	(0.019)	(0.017)	(0.015)	(0.017)	(0.021)	(0.046)
Catering	-0.007	-0.048**	-0.054***	-0.053**	-0.065***	-0.115*
	(0.020)	(0.020)	(0.016)	(0.023)	(0.024)	(0.064)
Electrical	-0.044***		0.057**	0.005	0.020	-0.040
	(0.010)		(0.023)	(0.043)	(0.038)	(0.062)
IT	-0.062***	-0.069***	-0.069***	-0.051***	-0.084***	-0.088***
	(0.010)	(0.023)	(0.011)	(0.014)	(0.014)	(0.018)
Tourism	-0.044***	-0.049**	-0.079***	-0.050***	-0.026	-0.083*
	(0.015)	(0.021)	(0.012)	(0.016)	(0.032)	(0.047)
Peer effects previous year		0.001		0.046***		0.008
		(0.020)		(0.018)		(0.046)
Class size		0.001		0.006***		0.003
		(0.001)		(0.002)		(0.003)
School budget per capita		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)
N[4]	1335	865	1285	886	1345	920

Table 4: Propensity Score Estimation

	2008-09	*2009-10*	*2010-11*
Dep. Var.	b/se	b/se	b/se
Extracurricular activities participation			
Male	0.018	-0.023	0.054
	(0.114)	(0.125)	(0.122)
Age	-0.295***	-0.162**	-0.166***
	(0.058)	(0.064)	(0.040)
Foreigner	-0.371	-0.510*	0.060
	(0.283)	(0.272)	(0.204)
Average mark previous year: 4-5.99	-0.274		-0.159
	(0.378)		(0.461)
Average mark previous year: 6-6.99	0.151	0.010	-0.360***
	(0.103)	(0.095)	(0.109)
Average mark previous year: 7-7.99	0.213	0.388***	0.145
	(0.176)	(0.126)	(0.145)
Average mark previous year: 8-10	0.338**	0.787***	0.258
	(0.166)	(0.181)	(0.223)
Constant	4.078***	1.915*	1.893***
	(0.919)	(1.052)	(0.667)
N	1410	1352	1347

Significance levels : $*$: 10% $**$: 5% $***$: 1%

In brackets std. err. clustered at class level.

The reference category for average mark previous year is failure.

For simplicity we omit the interactions terms and variables raised to the power.

Table 5: Effect of participation to extracurricular activities on High School dropout. Propensity score matching analysis.

		Coeff.	*(Std. Err.)*	*Observations*		
Algorithm				*Non Participants*	*Participants*	*Treated out of Common Support*
School Year 2008/09						
	Unmatched	-0.071***	(0.016)			
Nearest Neighbour, repl.	ATT	-0.040***	(0.007)	1034	375	1
Caliper=0.005	ATT	- 0.040***	(0.012)	1034	375	1
Radius, Caliper=0.005	ATT	-0.043***	(0.014)	1034	375	1
Kernel	ATT	-0.041***	(0.012)	1034	375	1
School Year 2009/10						
	Unmatched	-0.094***	(0.018)			
Nearest Neighbour, repl.	ATT	-0.069***	(0.007)	1005	344	2
Caliper=0.005	ATT	-0.069***	(0.014)	1005	340	6
Radius, Caliper=0.005	ATT	-0.072***	(0.015)	1005	340	6
Kernel	ATT	-0.075***	(0.013)	1005	344	2
School Year 2010/11						
	Unmatched	-0.041**	(0.021)			
Nearest Neighbour, repl.	ATT	-0.020	(0.012)	1070	277	0
Caliper=0.005	ATT	-0.020	(0.018)	1070	276	1
Radius, Caliper=0.005	ATT	-0.024	(0.017)	1070	276	1
Kernel	ATT	-0.030	(0.020)	1070	277	0

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Dependent variable: dropout. Treatment: Participation to extracurricular actives organised by the school.

Analytical standard error for the nearest neighbour algorithm. Bootstrapped standard errors for the other algorithms.

Table 6: Estimates sensitivity to the existence of hidden bias.

			Bias				
School Year	*Matching Algorithm*		$e^\gamma = 1$	$e^\gamma = 1.25$	$e^\gamma = 1.5$	$e^\gamma = 1.75$	$e^\gamma = 2$
2008-09	*N. N., with repl.*	Q^+_{MH}	2.293 **	2.767 ***	3.177 ***	3.543 ***	3.877 ***
	Caliper=0.005, with repl.	Q^+_{MH}	2.293 **	2.767 ***	3.177 ***	3.543 ***	3.877 ***
	Radius, Caliper=0.005, with repl.	Q^+_{MH}	4.139***	4.986***	5.713***	6.356***	6.936***
	Kernel	Q^+_{MH}	4.175***	5.027***	5.759***	6.406***	6.990***
2009-10	*N. N., with repl.*	Q^+_{MH}	3.965***	4.584 ***	5.127 ***	5.618 ***	6.069 ***
	Caliper=0.005, with repl.	Q^+_{MH}	3.933 ***	4.550 ***	5.090 ***	5.578 ***	6.027 ***
	Radius, Caliper=0.005, with repl.	Q^+_{MH}	4.941***	5.796***	6.534***	7.190***	7.782***
	Kernel	Q^+_{MH}	5.004***	5.866***	6.609***	7.269***	7.865***

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Q^+_{MH} represents the case when the average treatment effect is overestimated.

Table B1: Fixed Effect Model

	School years 2008-11	
	Coeff.	*St. Er.*
Age	0.048	(0.096)
2008-09	0.014	(0.097)
2009-10	0.051	(0.194)
2010-11	0.071	(0.289)
Extracurricular activities	0.055***	(0.016)
2008-09×Extracurricular activities	-0.057***	(0.019)
2009-10×Extracurricular activities	-0.121***	(0.020)
2010-11×Extracurricular activities	-0.104***	(0.028)
Outcome previous year		
Average mark previous year: 4-5.99	0.023	(0.064)
Average mark previous year: 6-6.99	0.025***	(0.009)
Average mark previous year:7-7.99	0.012	(0.009)
Average mark previous year:8-10	-0.003	(0.014)
Accounting and marketing	-0.088**	(0.037)
Surveying	-0.217*	(0.121)
Catering	-0.046***	(0.017)
IT	-0.156***	(0.035)
Tourism	-0.099***	(0.033)
Constant	-0.632	(1.438)
N	5566	

Significance levels : $*$: 10% $**$: 5% $***$: 1%