The Effect of Grants on University Drop-Out Rates: Evidence on the Italian Case

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ABSTRACT

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In this paper we evaluate the impact of need-based grants on university drop-out rates in the first year of enrollment, using student-level administrative data from all Italian universities in the period 2003-2013. We exploit the fact that not all eligible students receive financial aid due to limited resources to generate a treatment and a control group. Using this partition, we estimate the average treatment effect, i.e. the average effect on low income students, controlling for a set of observable characteristics by running regressions on blocks defined on the propensity score. Results point towards a sizeable effect of grants in reducing dropping out from higher education: around one third of these students would have left university in the first year in absence of the grants. This evidence is robust to a variety of specifications and sample selection criteria.

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1. Introduction

The aim of this paper is to evaluate the causal effect of need-based grants on the dropout rate among university students in their first year of enrollment. Household economic conditions and credit constraints may be reasons for being unable to afford university and for abandoning studies (Stinebrickner and Stinebrickner (2008)). Obtaining a grant, which covers university fees and living costs, may reduce the dropout probability by decreasing the direct and indirect costs of university attendance. In fact, the need to pay educational and living expenses imposes a strain on many students and their families that may encourage the student to leave university and start working in order to contribute to the household income. Moreover, the perceived benefits from higher education may be heterogeneous and it may be the case that expected benefits are lower for poor students (Zimmerman (2013)).

How to reduce university dropout rates is a matter of increasing concern: higher enrolment translates into a higher stock of human capital only if the propensity to quit before completion is low (Cappellari and Lucifora (2009); Zotti (2015)). This issue is particularly important in the Italian context. Italy has one of the lowest percentages of university graduates among European Union countries[1], due to both a low enrolment rate[2] and to high dropout rates (Di Pietro (2006); Cingano and Cipollone (2007)). In recent years the percentage of students dropping out has fallen[3] but it is still very high: the completion rate was 58% in 2013 (70% on average across OECD countries; ANVUR (2016)). Significant numbers of dropouts occur during the first year of study (Zotti (2015); Gitto et al. (2015); Mealli and Rampichini (2012)): between 2003 and 2014, on average, about 15% of new entrants to first level tertiary education[4] did not enrol for the second year, with a declining trend (from 16% in 2003 to about 12% in 2014; ANVUR (2016); De Angelis et al. (2016)).

We measure the impact of need-based aid on university dropout rates in the first year of enrollment by using student-level administrative data over the period 2003-2013 that cover the entire population of Italian university students. The data follow the student from his/her enrolment to graduation/dropout and provide several items of information on students' academic career and educational background. The key source of variation we exploit to identify the causal effect comes from funds rationing: some students eligible for the grant do not receive it due to limitation in the amount of funds. In fact, within each university, students are ranked according to an index of the family

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[1]Italy's first-time tertiary graduation rate is 35%, the fourth lowest among the OECD countries (OECD (2017)).

[2]Between 2007 and 2015 new entrants to first level programmes dropped by roughly 10% (De Angelis et al. (2017)).

[3]The reduction was partly a consequence of the 2001 reform (the "3+2" reform; Di Pietro and Cutillo (2008); Bratti et al. (2006); DHombres (2007); Cappellari and Lucifora (2009)). Indeed, one of the goals of the reform was to improve the performance of Italian university students, in terms of reducing both dropout rates and age at graduation (Bratti et al. (2010)).

[4]First level courses include three-year and five-year bachelor degrees.

economic condition: those below the cutoff for eligibility are awarded the grant up to exhaustion of the available funds. Then the methodology consists in comparing, within each university and controlling for the set of available observable, grant beneficiaries - the treated group - with eligible non beneficiaries - the control group. We do it in two steps: first we estimated the propensity score, defined as the probability of receiving treatment - the grant - given some student and university covariates. Then, the empirical strategy was based on blocking on the estimated propensity score in combination with regression adjustments within the blocks (Rosenbaum and Rubin (1983) and Rosenbaum and Rubin (1984)).

We find that being the recipient of a grant reduces the probability of dropout among low-income students by 2.7 percentage points (from 9.6%). Several robustness checks confirm this result: the estimated coefficients in the different specifications range from -2.7 to -4.3 percentage points. Our analysis also shows that the impact of the grant is heterogeneous depending on students' characteristics (area of residence, type of high school and final grade attained at high school) and on the share of eligible students in each university who actually receive the grant.

Information available in our database and the applied estimation strategy allow us to address several endogeneity concerns that could arise when investigating the causal impact of a grant on college persistence. One of the main issues is the difficulty in separating the unique effect of the grant from all the other factors that influence whether students succeed in college (Bettinger (2007)). In particular, family financial conditions determine the access to aid and are also directly associated with student outcomes[5]. However, in our setting beneficiaries and eligible students had very similar family characteristics: to be eligible for a grant certain thresholds in terms of the family's yearly income and assets must not be exceeded. Another endogeneity problem may arise when scholarships are (also) merit-based. In this case the estimate of the effect on dropout can be biased because students with scholarships perform better on average. For this reason, we only considered first year grants, which are only assigned on the basis of the household's financial situation: in this way beneficiaries should not be ex ante different in terms of a student's merit and abilities. Introducing a rich set of covariates into the matching procedure enabled us to control better for the remaining differences in terms of skills.

To date, research has preferred to examine the effect of financial assistance on enrolment[6], with respect to college completion, mainly because of the unavailability of longitudinal data with which to track students' success in college after initial enrolment and which make it possible to distinguish between transfers to other universities

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[5]Students from the poorest families tend to attend lower-quality high schools, have fewer resources for learning and, in general, parents who provide less support for their education.

[6]For example Lauer (2002); Kane (2003); Baumgartner and Steiner (2006); Cornwell et al. (2006); Goodman (2008); Steiner and Wrohlich (2012); Deming and Dynarski (2009); Nielsen et al. (2010); Vergolini and Zanini (2015).

and dropouts (Bettinger (2007))[7]. Due to lack of suitable data most empirical works focused on specific case studies, whose results are more difficult to generalize. Previous works undertaken in the Italian context relied on small samples of students in selected universities and academic years. Mealli and Rampichini (2012) used data from four Italian universities in 1999: by employing a Regression Discontinuity Design they showed that, at the threshold, the grant is effective in preventing low-income students from dropping out of higher education. Sneyers et al. (2016) considered first-year students at five universities located in Northern Italy in the academic year 2007-08; their findings suggested that financial aid positively affects students' performances and completion in a substantial and statistically robust way. The use of administrative data over a very long time span constitutes a major advantage of this paper with respect to previous works and a nice contribution for this literature.

As in our work, the majority of the existing studies have found a strong negative effect of need-based grants on the probability of withdrawing from college (Bettinger (2007); Castleman and Long (2016); Bettinger et al. (2012); Singell (2004b,a)), but a strong variability in the magnitude of the effect has emerged, that firstly depends on the population of the analysis and on the estimation technique[8].

The rest of the paper is organized as follows. Section 2 describes the grant assignment rule and Section 3 presents the data. Section 4 describes the empirical strategy and discusses the identification issues; the results are set out in Section 5. Section 6 concludes.

2. Grant assignment rule

The Italian financial aid system for higher education is mainly based on the *Diritto allo studio universitario* (DSU) program, intended to encourage enrolment and attendance by students from more disadvantaged families. The main objective of the DSU is to enable motivated students to obtain higher education, irrespective of their income (Prime Ministerial Decree, April 9, 2001). The main benefits offered by the DSU are student grants. After the 2001 constitutional reform, the DSU became part of the exclusive competence of regional legislation; grants are generally managed by regional agencies, with some administrative tasks assigned to universities[9].

Funds come from regional governments, from the central government (*Fondo Integrativo Statale*) and from a specific tax paid by non-eligible students. The amount of funding available for these grants thus differs among regions, years and also among universities within regions. There are remarkable differences between geographical areas

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[7]Other works have focused on different student outcomes: grades (Cappelli and Won (2016)) and time taken to complete a degree (Glocker (2011); Garibaldi et al. (2012); Denning et al. (2017); Fricke (2018)).

[8]Some recent studies have also examined the impact of merit-based grants on degree completion (Dynarski (2008); Scott-Clayton (2011)), but these scholarships target a population of students different from the one targeted by need-based grants.

[9]Calabria and Lombardy are the only regions where grants are entirely managed by universities.

due to the lower amount of funding available for the regions in the South of Italy: in 2013 the coverage rate was 90% in the North and 56% in the South (ANVUR (2016)). The percentage of eligible students who actually received the grant declined during the Great Recession: it was about 82% in the period 2006-08, it reached the minimum in 2011 (69%) and then increased to 76.5% in 2013.

In the first year of enrolment, eligibility for a grant is exclusively based on the student's family situation[10]. Applicants are ranked according to an index (the ISEE, which is an equivalized economic situation indicator), computed on the basis of the family's yearly income and assets and which also takes account of the family's composition. The allocative algorithm of the grants is thus a continuous function of this index but a maximum threshold is set at national level, that guarantees that only students from low income families are eligible. This eligibility threshold is pretty low, making the students comparable in term of financial condition even if the eligible student's index may fall close or far from it. As an example, in 2008 the ISEE cutoff for eligibility was around 19,000 euros. For a household with both spouses and one child, with zero assets, this is equivalent to a after-tax yearly income as large as 27,000 euros, which in turn is approximately equivalent to 77% of the average Italian yearly income that year for a household of that type.

However, not all eligible students receive the grants due to the lack of funds in some universities and for certain years. This constitutes the source of variation that provides identification in our paper and that allows us to generate a treatment group (those who actually received the grants) and the control one (eligible but not beneficiaries). Note, however, that beneficiaries are slightly poorer than eligible students not receiving the grant (because, as noted above, applicants are ranked according to the ISEE index). This implies that, if our identification strategy were not sufficient to compensate for the selection bias, the resulting bias is likely to be positive, i.e. against finding a negative effect of the grant on the drop-out rate.

The timing of the grants' assignment and the type of information available to students may cause selection along different dimensions, which must be taken into account in the analysis. First, if the assignment of the grant is known beforehand, the receipt of the grant may encourage enrolment by students with a low probability of academic success simply because the financial costs that they incur for their educations are artificially lowered. However, in Italy the application for a grant is submitted after enrolment to the regional agency where the university is located[11]; notice of acceptance is in general communicated a few months after enrolment.

Second, since the probability to receive a scholarship varies across region/year/university, in principle there is room for students to strategically self-select into universities with a higher coverage ratio. In practice, this strategic behavior is precluded because the

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[10]The second payment of the grant is conditional on the achievement of a minimum level of credits (established by the regions after consulting the universities, up to a maximum of 20 credits; Prime Ministerial Decree, April 9, 2001).

[11]In Calabria and in Lombardy the application is submitted directly to the university.

coverage rates are not public information, due to the delayed notice of acceptance. Students' strategic behaviour is based on past information, but the coverage rate varies widely over time because it depends on the availability of public funds and on political choices. Moreover, since we control for university/year fixed effects, this selection would have been a concern only if beneficiaries and eligible students within the same university had had a different set of information about coverage rates, i.e. if students' strategic behaviour had been correlated with ISEE scores.

The amount of the grant depends on whether students are resident in the city where the university is located, whether they are daily commuters or out-of-site students. Every year the Ministry of Education sets the minimum amount for a grant, but the differences over time are very small. For example, in 2013 the minimum yearly amounts for the three categories of students were, respectively, €1,904, €2,785 and €5,053; the average amount was about €3,400[12].

Even if not all the eligible students are awarded the grant, these students are all exempted from the payment of tuition fees. In 2013 the average yearly amount of tuition fees in state universities was about €1,000 (about €700 in the South and €1,400 in the North), and it was lower for students from low-income families (the lowest bracket was €200; ANVUR (2016)). Summing up, the average size of the grant is at least three times larger than the average fee eligible students are exempted from.

3. Data

We exploited the *Anagrafe Nazionale Studenti* (ANS), a unique dataset that contains administrative records on enrolments, students' school background and their academic careers in Italian universities. The by far main advantage of our database is that it covers the entire population of university students in Italy over a long spell of time. We focused on students aged between 18 and 20[13], enrolled for the first time at an Italian university over the period 2003-2013. Our working sample included first-year student recipients of grants, the treatment group, and those that were eligible but were not awarded the grant, the control group[14]. On average 19,000 students per year were recorded. Descriptive statistics of the sample are shown in Table 1. We defined dropout students as those enrolled as first year students in the academic year t who did not enrol at any university in the following academic year *t+1* (ANVUR (2016);

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[12]Source: *Osservatorio Regionale per l'Universita' e il Diritto allo studio universitario del Piemonte.*

[13]The rationale for this is to avoid problems of comparability between students who started university immediately after completing high school and those who started an undergraduate program later on.

[14]A potential problem with our comparison group is that it includes also students not eligible for the grant but exempted from paying the tuition fees for other reasons. Based on the information available in the archive we are unable to separately identify these students to exclude them from the analysis. Luckily, based on collateral evidence we can conclude that the resulting degree of contamination of the comparison group is negligible (we estimate they might be approximately 1-2% of the students included in the comparison group).

De Angelis et al. (2016); De Angelis et al. (2017)). The dropout rate was, on average, 7.6%, with a downward trend; recipients of grants represented about 70% of all eligible students. Table 2 reports the mean differences between the two groups (treated and non-treated), with respect to drop out rates and to some individual characteristics possibly affecting drop out rates (for example, gender, type of area of residence, school grades and type). The dropout rate is statistically lower for treated students. Also the other mean differences between treated and controls are significantly different for all the considered variable. We will obviously take them into account both in the propensity score matching and in the regressions, to compensate the selection bias.

4. Estimation strategy

We were interested in estimating the following equation on the sample of treated and control groups:

$$Y_{iut} = \alpha S_{iut} + \beta X_{iut} + \gamma D_{ut} + \epsilon_{iut}. \tag{1}$$

where student, university and year are indexed by i, u and t, respectively.

Y_{iut} is a dummy variable taking the value 1 if the student i enrolled at university u at time t dropped out at the end of the year.

S_{iut} is a binary treatment status denoting recipients of a grant: this dummy variable takes the value 1 if the student received a grant, and 0 if the student did not receive it despite being eligible for. In line with other studies (Adamopoulou and Tanzi (2017); Di Pietro (2004)), X_{iut} are individual characteristics possibly relevant for dropout rates, namely gender, nationality, area of residence (North, Centre, South), a dummy for studying in a macro area different from the area of residence, high school type and grade, and a dummy for the local urban labour system of residence (as a proxy for the economic status of the home town; see Table 2).

Finally, D_{uT} are university dummies interacted with period dummies, in order to capture university/period-specific patterns (we considered three periods: 2003-06, 2007-10 and 2011-13)[15]. Including these university-year fixed-effects in the regression we identify the causal parameter exploiting only the within-university/year variability in the treatment status.

α was our parameter of interest, the average impact of need-based financial aid on the dropout probability. Endogeneity issues may arise in the estimation of α. A classic problem in this literature is an ability bias due to selection into treatment of more able students. This would be a major concern if the grant was awarded (also) on the basis of student's merit. As explained, this is not the case for students enrolled in the first year of the program: in their case it is only the family economic circumstances to matter for the assignment of the grant. In addition, we were able to control for some factors relating to students' abilities and merits (high school type and grades). Another endogeneity issue that has frequently emerged in the literature relates to the

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[15]Results are robust to the inclusion of the interaction terms university*year.

fact that application for a grant is voluntary and the propensity to apply may depend on a set of observable and unobservable individual characteristics, possibly correlated to the outcome. This concern did not apply in our setting, because both the treated and the control groups were students that had voluntarily applied for the grant.

The main problem we face is how to control for differences in the economic circumstances of the student household. The assignment of the grant is based only on the ISEE index which unfortunately we do not observe in our dataset. Hence, all the household characteristics correlated to ISEE and to the outcome are confounders for our problem. What we do is to control for the set of characteristics of the student, of his household and of his university (including a university-year fixed effect). It should be noted, however, that if our strategy was not enough to net out the differences between the two groups with respect to financial conditions,the resulting bias is likely to be positive, i.e. against finding a negative effect of the grant on the drop-out probability.

To implement our estimator we proceed in two steps. First we estimated the propensity score defined as the probability of receiving treatment given some students' and universities' covariates (described in Table 2, plus university dummies interactions with period dummies):

$$e(X, D) = \mathbf{E}[S_{iut}|X_{iut}, D_{ut}] = Pr(S_{iut} = 1|X_{iut}, D_{ut}) \qquad (2)$$

where the estimator is based on a logit model.

Then, the empirical strategy is based on blocking on the p-score combined with regression adjustment. The idea behind this method, proposed by Rosenbaum and Rubin (1983) and Rosenbaum and Rubin (1984), is to split the sample into sub-classes according to the propensity score and then run the regression of the outcome on the treatment status as well as on the list of controls included in the p-score within each subclass. The two main advantages of this estimator are as follows (Imbens (2015)): first, the sub-classification approximately averages the propensity score within the sub-classes, smoothing over the extreme values of the propensity score; and second, the regression within the sub-classes adds a large amount of flexibility compared with a single weighted regression.

Following Imbens (2015), we need to partition the range [0,1] of the propensity score into J intervals $[b_{j-1}, b_j)$, for $j = \{1, \ldots, J\}$, where $b_0 = 0$ and $b_J = 1$. Let $B_i(j) \in \{0, 1\}$ be a binary indicator where the estimated propensity score for unit i, $\hat{e}(x)$, satisfies $b_{j-1} < \hat{e}(x) < b_j$. In particular, we choose to partition the sample into 5 blocks according to the following propensity score values: j=1 if $0 \leq \hat{e}(x) < 0.2$; j=2 if $0.2 \leq \hat{e}(x) < 0.4$; j=3 if $0.4 \leq \hat{e}(x) < 0.6$; j=4 if $0.6 \leq \hat{e}(x) < 0.8$; j=5 if $0.8 \leq \hat{e}(x) \leq 1$.

Within each block the average treatment effect is estimated using linear regression with all of the covariates X_{iut} and D_{uT} described in equation (1), and including an indicator for the treatment. By including in each regression the university-year fixed-effects we identify the average causal effect relying only on the within-university-year variability of the treatment status: the comparison group is made up of students en-

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rolled at the same university in the same period as the treated one. Standard errors are corrected for the potential clustering of residuals at the field of study level. This leads to J estimates $\hat{\alpha}_j$, one for each block. These J within-block estimates are then averaged over the J blocks, using the proportion of treated units in each block as the weights:

$$ATT = \alpha_{block,treat} = \sum_{j=1}^{J} \frac{N_{treatj}}{N_{treat}} \cdot \hat{\alpha}_j \tag{3}$$

The coefficient $\alpha_{block,treat}$ is the estimated value of the average effect of the grant on the probability to drop out for those receiving the grant, i.e. we estimate the average treatment effect on the treated group (ATT). Of course, to explore the degree of heterogeneity of the causal effect one could also evaluate the weighted average with respect to a different set of weights, e.g. the proportion of untreated units in each block, so as to get the average treatment effect on those not receiving the grant (ATNT) or the proportion of units in the block to get the average treatment effect on the population (ATE).

5. Results

Figure 1 plots the distribution of the propensity score for the two groups. A large difference between the two groups is apparent with treated units closely concentrated just below 1 and untreated units more evenly distributed over the whole support with a mode of around 0.2. The mean (median) value of the propensity score is 0.85 (0.95) for treated students and 0.37 (0.29) for untreated ones. The large difference between the two distributions might rise a concern about the lack of common support. Note however that the large number of units available in both groups make the comparison feasible essentially every where on the support of the p-score. In particular, in the last block, where the proportion of non-treated units is the tiniest, we have about 6,100 students in the comparison group. The main driver of this large difference between the two distributions is the university-year fixed-effect (see also Section 5.2). As explained in the previous section, there is a strong case for including these fixed-effects among the control variables: in this way, in fact, we can force the composition of the comparison group with respect to university/period to be exactly the same as for the treatment group.

Table 3 reports the estimated effect of the grant for each block ($\hat{\alpha}_j$) and the weighted average effect (ATT), while Table 4 presents the estimated coefficients for all the variables included in the regression in each block. We find that the receipt of a grant has a negative and significant effect on the dropout rate for the treated students: the estimated average effect is a reduction of 2.7 percentage points in the probability of dropping out (with a standard error of 0.0036). This is very close to the crude difference in the dropout rate that we observe between the two groups in Table 2, meaning that the large differences with respect to observable characteristics summarized by the

propensity score in this instance do not raise any substantial selection bias problem. Since most of these observable characteristics do matter for the dropout rate (see in particular the last column of table 4), it must be that the selection bias separately due to each of these observable characteristics overall cancels out. The magnitude of the estimated coefficient is significant: the dropout rate for those who received the grant would have increased from 7% to about 10% in the absence of a grant.

In regard to the within-block estimates, the average effect is driven, as expected, by the fifth block (which includes 78% of treated students). On the contrary, the coefficients of the first three blocks are positive or not significantly different from zero; this may be explained by students' characteristics: in particular, in these blocks there are higher percentages of students from *licei* and who reported high grades at school. For these students, the effect of the grant, as explained in Section 5.1, is smaller[16].

As a robustness check we further split the last block (Table 3, bottom panel): first we halved it and we obtained an average impact of -3.0 percentage points (standard error 0.0041); we then further divided the last block in half, resulting in an average total effect of -3.5 percentage points (standard error 0.0046).

As regards the other possible determinants of dropout, our results are in line with the findings of other studies (Adamopoulou and Tanzi (2017); Di Pietro (2004)): females, students from *licei*, those with better high school grades, out-of-site students and those living in the North are less likely to dropout (Table 4).

As we said previously, one of the main advantages of our analysis was that we could rely on longitudinal data which allowed us to track the student after enrolment. Using this feature of the database, we checked whether the grants obtained in the first year also had an impact on subsequent years' outcomes. In particular we evaluated the impact of the grant on time to graduation. We find that the receipt of the grant has a positive and statistically significant effect on the probability to graduate within the legal duration of the course or few years longer (Table 5). The results suggested that first-year grants, in addition to reducing the drop-out rate immediately, also encourage students to finish their studies within a set time.

5.1. Heterogeneous effects

Both the opportunity costs and the expected benefits of higher education may differ according to students' characteristics and to their family and educational backgrounds. Therefore in this section we analyse the heterogeneity of the average impact of the grant (Table 6; we report the average impact computed as in equation (3)[17]). We first interacted the treatment status with the female dummy and found that the coefficient

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[16]The positive sign of the coefficient in block 1 is also driven by students enrolled at the University of Genoa, for whom the measurement error in the treatment variable was particularly large (see Section 5.2 for further details). When we excluded these students from the working sample, the estimated coefficient in the first block became negative and not significant, but the average coefficient in the baseline regression remained substantially unchanged. Results are available upon request.

[17]Results remain unchanged if we estimate all the interactions simultaneously.

of the interaction term was not statistically significant, thus suggesting that the impact of the grant does not vary by gender.

Second, we wanted to assess whether there are any differences in the impact according to the area of residence. The coefficient on the interaction term revealed that students resident in the South of Italy gain more from financial aid than students resident in the other areas. In particular, the drop-out rate would increase in absence of the grant from 6.5 to 10.8% for students in the South of Italy and from 7.2 to 8.5% for those resident in the Centre and North. A possible explanation is that budget and credit constraints are more likely to be binding in the South, which is the poorest area of Italy.

In order to deal with differences in the family and educational background, which affect both the opportunity costs and the expected benefits of higher education, we interacted the treatment status with dummies for high school type, which can also be considered a proxy for the family background, since in Italy social mobility is very low (Mocetti (2007); Checchi et al. (1999)). Without the grant the dropout rate would increase from 4.3 to 5.5% for students from *licei* and from 10 to 14.5% for students from vocational studies. These students benefit more from the financial aid, since they may have lower expected benefits in attending university. In the same way, more able students have higher expected benefits from obtaining a university degree and thus are less likely to dropout irrespective of the grant: without the grant the dropout rate would increase from 3.8 to 4.7% for students who reported a high grade at the final exam of the high school and from 8.7 to 12.2% for low grade students[18].

The impact of the grant may also vary according to the share of eligible students who actually receive a grant. In fact, marginal recipients enrolled at universities where the coverage rate is low can be poorer than those enrolled at universities where almost all eligible students receive a grant and therefore the average impact of the grant on them is likely to be larger. This issue is particularly relevant in our analysis given the geographical divide in coverage rates, which are much smaller in Southern universities [19]. In order to check this hypothesis, we interacted the treatment dummy (S_{iuT}) with ($CR_{ut} - CR_{avr}$), which is the difference between the coverage rate at university u in period t and the average coverage rate. In this specification of the model the coefficient on the treatment dummy represented the causal effect of a grant for students in a university/period with a coverage ratio at the average level, while the coefficient on the interaction term represented the change in the causal effect of a grant induced by a marginal variation of the coverage rate with respect to the average.

The sign of the interaction term is negative in all blocks but the third one (Table 7): an increase in the coverage ratio leads to a statistically signicant increase in the impact of grants on dropout rates. The interaction term is particularly large and statistically

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[18]The minimum high school grade is 60, the maximum is 100.

[19]On average, almost 60% of the eligible students enrolled at university in the South of Italy obtained a grant, compared with more than 80% of the eligible students in the North.

significant for blocks 2 and 4, where the coverage ratio is lower than the average, while it is much smaller (and statistically insignificant) for block 5 where the share of students receiving the grant is higher than the average. Block 3 stands out with respect to this pattern, a possible explanation being its geographical composition: there are far more (less) students from Central and Northern (Southern) regions of Italy than in the other blocks. Overall, it seems that an increase in the coverage ratio in the universities where it is below the average would be beneficial.

In a heterogeneous response model, the treated and non-treated may benefit differently from being awarded a grant, therefore the effect of the treatment on the treated will differ from the effect of the grant on the untreated, hence from the average treatment effect. To explore the degree of heterogeneity of the causal effect we computed the effect of the grant using different weighting strategies. We first use the proportion of untreated units in each block as a set of weights to get the average treatment effect on those not receiving a grant (ATNT): in this way we gave most weight to the left tail of the propensity score distribution, and in particular to the second block (see Figure 1), where the coefficient of the treatment dummy is not statistically significant (see Table 4 and Section 5). Consequently, the average coefficient becomes approximately zero and statistically not significant. Secondly, we computed the population's average treatment effect (ATE), which would be the average causal effect if eligible individuals were assigned at random to treatment. We used the share of units in each block as a set of weights to average out block coefficients and we found that the effect of the grant on the whole population of low income students is a reduction in the dropout rate of 1.9 percentage points (with a standard error of 0.002).

5.2. Robustness

We now present a set of robustness analyses in order to check whether our results hold over a variety of specifications and sample selection criteria.

The first two robustness checks were connected to the estimation of the propensity score (PS as in equation (2)). First, as shown in Figure 1, the distribution of the PS is highly unbalanced in the two treatment arms, due to the inclusion of university/period fixed-effects that capture most of the variability in the treatment status. If we remove these fixed-effects, and only include time fixed-effects, we obtain a more balanced distribution (Figure 2). The average impact of a grant on dropout rate for the treated (ATT) is still negative and statistically significant, even if the magnitude is lower (1.15 percentage points, with a standard error of 0.0013; Table 8). It is important to note that in the baseline model presented in Table 3, the composition of the comparison group with respect to the university/period is forced to be the same as for the treatment group. This is no longer the case when we drop the university fixed effect, leaving only the period fixed effect.

Second, in the baseline model the treated and the control units are enrolled in the same university and in the same period, but possibly in different fields of study. Funds rationing do not follow some specific pattern across field, but in any case it could be important to control for field specific characteristics. Therefore we expanded

the fixed effects and made them university*time*field-specific, considering four fields: sanitary, scientific, social and humanities [20]. Results are confirmed: the estimated ATT is -0.0276 (with a standard error of 0.0034).

Third, we replicated the analysis by using two alternative estimation procedures: kernel matching and propensity score re-weighting. In both cases we included the X_{iut} and D_{uT} controls described in equation (1). The results are reported in Table 9. Using the kernel matching method[21] (with a bandwidth of 0.06 and with bootstrap standard error[22]), the estimated average treatment effect on the treated group is -4 percentage points (bootstrap standard error 0.0037); following the propensity score re-weighting (where weights equal 1 for treated students and $\hat{e}(x)/(1-\hat{e}(x))$ for the control group) the estimated effect of a grant is -3.9 percentage points (with a robust standard error of 0.0058). These are basically the values of the estimated ATT we presented in Table 4 when breaking down the fifth block into three sub-blocks.

The fourth robustness check examined the presence of possible measurement errors in the treatment status. According to the statistical office of the Ministry of Education, University and Research (MIUR), and considering all enrolled students, the rate of students with grants was on average 7.4% over the period 2003-13 (ANVUR (2016)), while according to ANS data the rate was lower, about 5% of all enrolled students[23]. The difference could be mainly due to the fact that data on grants are collected from different sources. ANS data are administrative data reported by universities while MIUR data are provided by the regional agencies that manage grants. These differences in the data could generate two problems relating to possible measurement error in our treatment variable. The first is a non random selection of the students awarded grants that occurs if the students with grants that are not reported in our database are not randomly selected in terms of students' or universities' characteristics. Since we are able to control for a large set of variables at the individual and university level, we do not think that this issue compromises the validity of our results. The second problem is contamination and it occurs if the control group includes some treated individuals; this would imply that we are underestimating the impact of a grant on the drop out rate. To deal with this issue, we restricted the sample of our analysis in order to minimize the gap between ANS and MIUR data. In particular, we restricted the sample by only considering university-year pairs for which the difference between the two data sources was minimal (in particular, we only kept the universities for which the difference

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[20]The sanitary field includes medicine, pharmacy, veterinary medicine; the scientific field includes math, physics, statistics, geology, biology, engineering, architecture, computer science; the social field includes political/social sciences, law, economics and management; humanities include literature, languages, history, geography.

[21]The extent of balancing between the two samples significantly increases after matching is carried out. After matching, the pseudo R2 reduces to 0.05 from 0.43 and the mean bias to 3.0 from 9.5.

[22]We replicated the analysis with bandwidths of 0.08 and 0.04 and the results remain unchanged.

[23]Unfortunately, we cannot make these comparisons on grants for our working sample since there are no publicly available statistics for the sample of 18-20 year old students enrolled for the first time in Italian universities.

between the two databases in the number of students awarded grants was lower than 5%). Table 9 shows the results: the negative and statistical significant impact of grant is confirmed, with an average effect of -4.3 percentage points (standard error 0.0059).

Considering all the results yielded by our analysis, the estimated impact of grants on beneficiaries is a reduction in the dropout probability that ranges from -2.7 percentage points in the baseline analysis to -4.3 percentage points in the most stringent specification.

6. Conclusions

In this paper we have explored the effects of Italian university need-based grants on student dropout rates in the first year of enrolment. Our focus on dropout is determined by the importance of this phenomenon in Italy: only about 60 per cent of students who enrol obtain a university degree (Gitto et al. (2015)) and the majority of dropouts occur at the end of the first year of enrolment (Mealli and Rampichini (2012)). The main advantage of our analysis is that it is based on a unique database covering the entire population of university students in Italy. The paper addresses endogeneity issues by restricting the sample to eligible students and by exploiting the fact that, due to insufficient funds, some of them are not awarded a grant. A blocking with regression adjustments estimation strategy further refined the comparison by partitioning treated and control students within blocks based on their propensity score. We found that the grants help in preventing students from low-income families from dropping out of higher education. The estimated effect is sizeable: the dropout rate for low-income students would rise from about 7% to 10% as a consequence of not receiving a grant. The result is quite robust to different estimation methods and also holds when we restricted the sample for further robustness checks.

As for the policy implications of the paper, our analysis confirms the role of financial constraints in explaining large differences in university dropout rates: reducing the dropout rate of students from low-income families can lead to more equitable schooling opportunities, thus improving educational mobility across generations. Moreover, low university completion rates have an impact on several outcomes (OECD (2016)): educational attainment affects participation in the labour market (the employment rate of tertiary graduates is higher than that of upper-secondary students) and earnings, and it influences social outcomes (good health, life satisfaction). University completion is particularly important in Italy, given the "legal" value of university degrees (in terms of access to public-sector jobs and to specific regulated occupations) and the honorific title of "dottore" which conveys an important social status (Cappellari and Lucifora (2009)). All these aspects reinforce the need to augment college graduation rates, in terms of both increasing enrolment and reducing dropout rates.

13

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Tables and figures

Table 1: Descriptive statistics of the working sample by year of enrollment.

	2003-06	2007-10	2011-13
Pct. of dropouts	8.2	7.6	6.7
Pct. of recipients of grants	68.1	73.6	72.6
Pct. of females	63.3	62.8	62.1
Pct. of residents in the North	26.8	32.5	31.4
Pct. of residents in the Centre	15.4	17.6	16.5
Pct. of residents in the South	57.8	49.9	52.1
Average high school grade	85.0	82.8	83.5
Pct. from *licei*	51.7	59.5	62.3
Pct. of out-of-site	13.9	18.0	21.3
Pct. living in an urban LLS	39.8	39.8	40.0
Pct. of foreign students	1.4	3.4	4.4
N (annual average)	20,918	19,149	14,985

Source: our calculations based on ANS data.

Notes: The working sample includes students aged between 18 and 20, enrolled for the first time at an Italian university, who were eligible for the grant (all of them are exempted from paying tuition fees).The variable high school grade consists in the grade reported at the final exam of high school: the pass level is 60, top level is 100.

Table 2: Descriptive statistics for treated and non-treated groups.

	Treated	Non-treated	Differences
Pct. of dropouts	6.9	9.6	-2.7***
			(0.1)
Pct. of females	63.8	60.6	3.2***
			(0.2)
Pct. of residents in the North	32.3	24.1	8.2***
			(0.2)
Pct. of residents in the Centre	17.8	12.8	5.1***
			(0.2)
Pct. of residents in the South	49.8	63.1	-13.3***
			(0.2)
Average high school grades	83.3	85.3	-2.0***
			(0.1)
Pct. from *licei*	55.2	61.3	-6.1***
			(0.2)
Pct. of out-of-site	2.15	6.11	15.4***
			(0.2)
Pct. living in an urban LLS	38.8	42.5	-3.8***
			(0.2)
Pct. of foreign students	3.5	1.0	2.5***
			(0.1)
N	146,005	59,219	

Source: our calculations based on ANS data.
Notes: Years 2003-13. Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure 1: Distribution of the propensity score in the treated and non-treated group
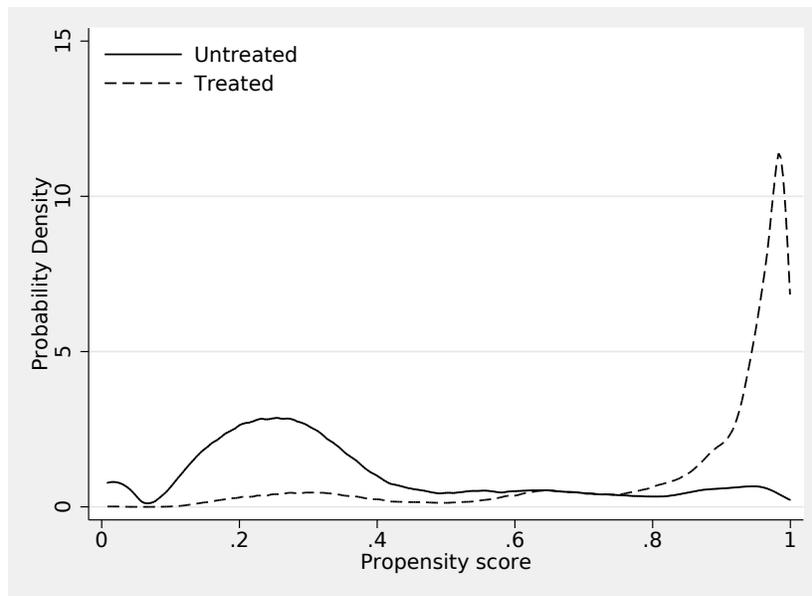
Notes: The following controls are included in the p-score: female, area of residence (North, Centre, South of Italy), foreign, a dummy for studying in an area different from that of residence, high school type (dummies for different types) and grade (categorical variable with 5 classes), a dummy for residing in an urban local labour system, and university dummies interacted with year dummies.

Table 3: Estimated effect of grants on dropout rate.

block #	weight	α_j	standard error
j=1	0.0158	0.0256***	0.0075
j=2	0.0762	0.0008	0.0035
j=3	0.0382	-0.0047	0.0053
j=4	0.0916	-0.0236***	0.0049
j=5	0.7781	-0.0323***	0.0046
ATT		-0.0270***	0.0036
Robustness checks with different partitions of the sample			
j=5	0.1180	-0.0228***	0.0066
j=6	0.6601	-0.0391***	0.0060
ATT		-0.0303***	0.0041
j=5	0.1180	-0.0228***	0.0066
j=6	0.1610	-0.0247***	0.0080
j=7	0.4992	-0.0530***	0.0086
ATT		-0.0350***	0.0046
N	205,147		

Source: our calculations based on ANS data

Notes: The average effect (ATT) is computed as the weighted average over the J blocks, using the proportion of treated units in each block as weights (equation (3)). Each within-block regression includes the following controls: female, area of residence, foreign, a dummy for studying in an area different from that of residence, high school type and grade, a dummy for residing in an urban local labour system, and university dummies interacting with period dummies. Residuals are clustered at the field of study level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: Estimated effect of grants on dropout rate. Full regression.

| | | Dep. var: dummy dropout | | | |
	(block 1)	(block 2)	(block 3)	(block 4)	(block 5)
grant	0.026***	0.001	-0.005	-0.024***	-0.032***
	(0.007)	(0.004)	(0.005)	(0.005)	(0.005)
females	-0.005	-0.016***	-0.007	-0.004	-0.007***
	(0.005)	(0.004)	(0.006)	(0.005)	(0.002)
residents in the Centre	0.046	-0.032*	0.035**	-0.004	0.023***
	(0.032)	(0.017)	(0.014)	(0.013)	(0.003)
residents in the South	0.009	0.012	0.004	0.004	-0.002
	(0.034)	(0.017)	(0.020)	(0.012)	(0.003)
foreign student	0.034	-0.021	-0.013	-0.027	-0.029***
	(0.081)	(0.030)	(0.022)	(0.017)	(0.003)
out-of-site student	-0.086***	-0.025*	-0.003	-0.025**	-0.007**
	(0.025)	(0.013)	(0.012)	(0.011)	(0.003)
high school grade	-0.036***	-0.033***	-0.027***	-0.022***	-0.021***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
vocational high school	0.116***	0.091***	0.083***	0.054***	0.050***
	(0.007)	(0.005)	(0.008)	(0.005)	(0.002)
other high school	0.137***	0.126***	0.076***	0.063***	0.065***
	(0.010)	(0.007)	(0.009)	(0.007)	(0.003)
living in an urban LLS	-0.002	0.011***	0.001	0.007*	0.006***
	(0.005)	(0.004)	(0.006)	(0.004)	(0.002)
University/period FE	YES	YES	YES	YES	YES
R-sq	0.076	0.059	0.065	0.063	0.054
N (treated)	2,313	11,124	5,575	13,373	113,577
N tot	16,749	38,247	11,822	18,607	119,722

Source: our calculations based on ANS data.
Note: Omitted categories are: high school *licei* and students resident in the North of Italy. High school grade is a categorical variable with 5 classes. Standard errors clustered at the field of study level in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Share of graduates within x years of the legal duration of the course.

	Treated	Non-treated	Differences
within 1 year	0.527	0.430	0.097***
			(0.003)
within 2 years	0.577	0.486	0.090***
			(0.003)
within 3 years	0.604	0.519	0.085***
			(0.003)
within 4 years	0.618	0.537	0.081***
			(0.003)
N	110,199	45,383	

Source: our calculations based on ANS data
Notes: * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Estimated effect of grants on dropout, interaction terms.

	Estimated average impact (ATT)			
	(1)	(2)	(3)	(4)
treatment	-0.0315***	-0.0123***	-0.0455***	-0.0355***
	(0.0056)	(0.0041)	(0.0059)	(0.0045)
treatment*female	0.0075			
	(0.0067)			
treatment*resident South		-0.0311***		
		(0.0075)		
treatment*$licei$			0.0335***	
			(0.0066)	
treatment*high school grade				0.0263***
				(0.0058)
N	205,147	205,147	205,147	205,147

Source: our calculations based on ANS data

Notes: The table reports the ATT: the average impact computed as the weighted average over the J blocks, using the proportion of treated units in each block as weights (equation (3)). Each within-block regression includes the following controls: female, area of residence, foreign, a dummy for studying in an area different from that of residence, high school type and grade, a dummy for residing in an urban local labour system, and university dummies interacted with year dummies. Residuals are clustered at the field of study level. * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Estimated effect of grants on dropout, interaction with the coverage rate.

block #	weight	α_j	standard error	β_j	standard error
$j=1$	0.0158	0.0147	0.0735	-0.0211	0.1440
$j=2$	0.0762	-0.0443**	0.0212	-0.1090**	0.0530
$j=3$	0.0382	-0.0044	0.0092	0.0012	0.0490
$j=4$	0.0916	-0.0277***	0.0051	-0.1128**	0.0524
$j=5$	0.7781	-0.0234*	0.0139	-0.0451	0.0669
N	205,147				

Source: our calculations based on ANS data

Notes: α_j is the coefficient of the treatment variable; β_j is the coefficient of the interaction term between S_{iuT} (the treatment dummy) and $(CR_{uT} - CR_{avr})$ (the difference between the coverage ratio at university u in period T and the average coverage ratio). Each within-block regression includes the following controls: female, area of residence, foreign, a dummy for studying in an area different from that of residence, high school type and grade, a dummy for residing in an urban local labour system, and university dummies interacted with year dummies. Residuals are clustered at the field of study level. * p<0.10, ** p<0.05, *** p<0.01.

Table 8: Estimated effect of grants on dropout, with year fixed-effects (without university/period fixed-effects).

block #	weight	α_j	standard error
$j=1$	0.0018	-0.0157*	0.0092
$j=2$	0.2110	-0.0220***	0.0021
$j=3$	0.2951	-0.0114***	0.0023
$j=4$	0.4495	-0.0076***	0.0023
$j=5$	0.0425	-0.0017	0.0058
ATT		-0.0115***	0.0013
N	340,205		

Source: our calculations based on ANS data

Notes: The average effect ATT is computed as the weighted average over the J blocks, using the proportion of treated units in each block as weights (equation (3)). Each within-block regression includes the following controls: female, area of residence, foreign, a dummy for studying in an area different from that of residence, high school type and grade, a dummy for residing in an urban local labour system, and university dummies interacted with year dummies. Residuals are clustered at the field of study level. * p<0.10, ** p<0.05, *** p<0.01.

Figure 2: Distribution of the propensity score, with year fixed-effects (without university/period fixed-effects).
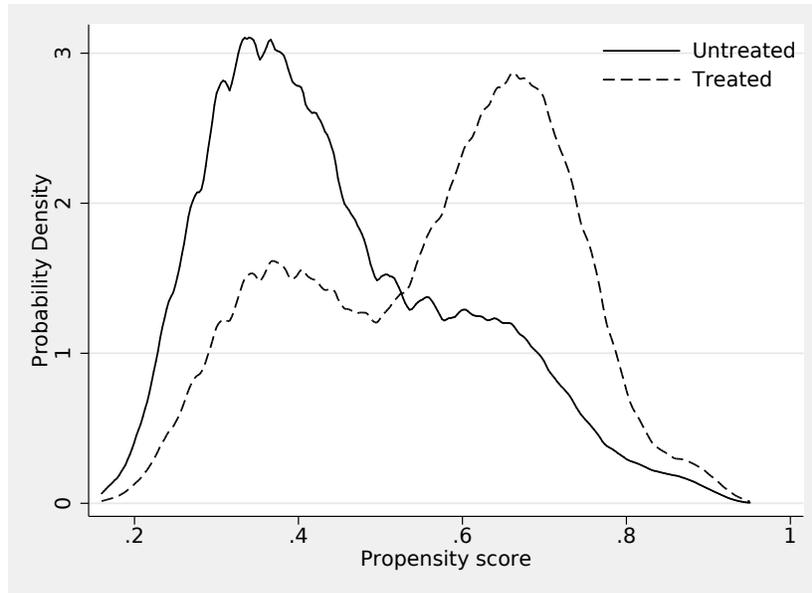
Source: our calculations on ANS data.

Notes: We included the following controls: female, area of residence, foreign, a dummy for studying in an area different from the one of residence, high school type and grade, a dummy for residing in an urban local labor system, year fixed-effects.

Table 9: Estimated effect of grants on dropout. Robustness checks with different estimation methods and different sub-sample.

	α	standard error
Different estimation methods		
Kernel matching	-0.0397***	0.0037
Propensity score re-weighting	-0.0389***	0.0059
N	204,759	
Different sub-sample		
Universities/years with low gap	-0.0431***	0.0060
N	119,131	

Source: our calculations based on ANS data

Notes: We included the following controls: female, area of residence, foreign, a dummy for studying in an area different from that of residence, high school type and grade, a dummy for residing in an urban local labour system, universities dummies interacted with year dummies. Residuals in the propensity score re-weighting are clustered at the field of study level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Different estimation methods: kernel matching is estimated with a bandwidth of 0.06 and with bootstrap standard error. Different sub-samples: the analysis is based on blocking with regression adjustments. The average effect (ATT=α) is computed as the weighted average over the J blocks, using the proportion of treated units in each block as weights.