On the Design of Grant Assignment Rules

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Abstract

The effect of grants on several academic outcomes has been widely studied, finding that they reduce the probability of dropping out of college. In this paper we go one step further by studying how to design rules for grant assignment. We assess how different rules affect dropout rates, as well as the characteristics of the recipients of the grants and the dropouts. The analysis uses administrative data from all Italian universities in the period 2003-13. Preliminary findings show that assigning the grants to those students with the highest estimated increase in the probability of continuing into the next year would reduce dropout rates by two percentage points, over a quarter of the total number of dropouts.

Keywords: Grants, Treatment Assignment

JEL classification: C25, I21, I22

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1 Introduction

Students in higher education incur into substantial costs, including fees, housing or the opportunity cost of not working for several years. Grants constitute a way to mitigate these costs, inducing more students to enroll at the university and completing a degree. They are particularly relevant for students whose families are not wealthy, as they are often credit constrained and are forced to abandon their studies before they obtain a university degree (Stinebrickner and Stinebrickner, 2008; Deming and Dynarski, 2009). Consequently, grants have typically been assigned on the basis of merit, aimed at high-performing students (*e.g.* Schudde and Scott-Clayton, 2016), or on financial grounds, aimed at students with low socio-economic status (*e.g.* Fack and Grenet, 2015).

Funds available for grants are limited. Thus, it is crucial to award grants appropriately. On the one hand, policy makers could focus on efficiency. For example, they could award grants to students who are high performers or to those who would finish their degree when they are awarded a grant but would drop out otherwise. On the other hand, grants also give students with a disadvantaged background the chance to access higher education. Hence, the policy maker should take both considerations into account when designing the rule to award them.

In this setting, this paper makes the following contributions. First, we estimate the probability that each student graduates depending on whether they are assigned an grant or not. Second, we study how different assignment rules affect dropout rates for the population as a whole, and for different subpopulations. Third, we characterize who are the recipients of the grants under different assignment rules.

The potential outcomes framework is the most natural choice to evaluate the effect of a grant on the probability of completing college education. It allows us to split the population of students into three types: those who would obtain their university degree even without a grant, those who would drop out even with a grant, and those who would obtain it only when they are awarded a grant. The latter conforms the group that benefits from the grant, so awarding grants to these students would be an effective use of funds. On the other hand, the first two types represent two different kinds of ineffective uses of grants funds, since their outcome is not affected by the grant.

Although it is not possible to determine whether a student would benefit from the grant, it is possible to estimate the probability that they graduate with and without the grant. The difference between these two probabilities represents the expected increase in the probability of graduating due to the grant. This information allows policy makers to weigh in the efficiency of the grant against making grants available for students with little financial means.

The effects of student financial aid on different outcomes have been thoroughly studied in the literature.[1] Many works have studied the effect of a grant on the probability of dropping out (Singell, 2004; Bettinger, 2004; Bettinger et al., 2012; Mealli and Rampichini, 2012; Castleman and Long, 2016; Denning, 2018). Moreover, several other papers have estimated the effect of obtaining a grant on other outcomes, such as enrollment (Baumgartner and Steiner, 2001; Lauer, 2002; Kane, 2003; Cornwell et al., 2006; Goodman, 2008; Deming and Dynarski, 2009; Nielsen et al., 2010; Steiner and Wrohlich, 2012; Vergolini and Zanini, 2015), grades (Cappelli and Won, 2016), or time to finish the university degree (Glocker, 2011; Garibaldi et al., 2012; Denning et al., 2017). However, none of these papers have addressed the question of how to appropriately assign grants. As far as we know, we are the first to do it by considering the effect of different assignment rules on completion rates for the overall population and specific subpopulations, as well as other measures that a policy maker could be interested in.

In this paper we focus on the Italian case, which is an interesting case study because the country has the lowest percentage of university graduates among the European Union countries, due to both a low enrollment rate and to high dropout rates. Also the availability of public grants is very limited compared to these countries. Thus, understanding the most appropriate mechanism of awarding grants turns out particularly useful.

Previous works undertaken in the Italian context found that students' performances and completion rates are strongly and positively affected by grants. Modena et al. (2018) found

[1] See e.g., Dynarski and Scott-Clayton (2013) for a review on how such programs work.

that around one third of the low income students would have left university in the first year in absence of the grants. Also other works about Italy (Mealli and Rampichini, 2012; Sneyers et al., 2016) find positive strong effects of the grants, but they rely on small samples of students in selected universities and academic years.

Differently, we measure the impact of need-based aid 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 enrollment to graduation/dropout and provide several items of information on students' academic career and educational background. The use of administrative data over a very long time span constitutes a major advantage of this paper with respect to previous works.

Preliminary results indicate that awarding grants to students increase graduation rates: given a grant to every student relative to giving it to none would reduce dropout rates by almost 25%, with a large variation on the effect across students. On the other hand, given a fixed number of grants that can be awarded, an efficient assignment rule would reduce the dropout rates relative to the baseline scenario from 7.6% to 5.6%.

The rest of the paper is organized as follows. The institutional details of the Italian system or higher education and the data used in this paper are respectively described in Sections 2 and 3. The empirical strategy is discussed in Section 4, whereas the results of the effect on grant on the probability of obtaining a college degree are presented in Section 5. On the other hand, Section 6 compares the outcomes of the different assignment rules. Finally, Section 7 concludes and enumerates the following steps to be taken.

2 Institutional Details

In the first year of enrollment, eligibility for a grant is exclusively based on the student's family situation. Within each university, students are ranked according to an index of the family economic condition: those below the cutoff for eligibility are awarded the grant up to exhaustion of the available funds. 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. However, not all eligible students receive the grants due to the lack of funds in some universities and for certain years. Even if not all the eligible students are awarded the grant, these students are all exempted from the payment of tuition fees. The average size of the grant is at least three times larger than the average fee eligible students are exempted from.

In Italy the amount of funding available for these grants differs among regions, years and also among universities within regions. There are remarkable differences between geographical areas due to the lower amount of funding available for the regions in the South of Italy. These funds come from regional governments, from the central government and from a specific tax paid by non-eligible students and are generally managed by regional agencies. 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.

3 Data

We exploited the Anagrafe Nazionale Studenti (ANS), a unique dataset that contains administrative records on enrollments, 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, enrolled for the first time at an Italian university over the period 2003-13. 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.

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. On average 19,000 students per year were recorded. Descriptive statistics of the sample are shown in Table X. We defined dropout students as those enrolled as first year students in the academic year t who did not enroll at any university in the following academic year *t+1* (ANVUR, 2016; Modena et al., 2018). The dropout rate was, on average, 7.6%, with a downward trend; recipients of grants represented about 70% of all eligible students.

4 Empirical Strategy

Let $Y_{it\tau}$ be a dummy variable that takes value 1 when student i successfully completes the τ-th year of a university degree at time t, and $D_{it\tau}$ be another dummy variable that equals 1 when student i is awarded an grant. This relation can be modelled as

$$Y_{it\tau} = q\left(D_{it\tau}, X_{it\tau}, \epsilon_{it\tau}\right) \tag{1}$$

where $X_{it\tau}$ is a vector of some observed characteristics, including a set of time and university effects, and $\epsilon_{it\tau}$ be an idiosyncratic disturbance term. The assignment of grants outlined in Section 3 suggests that the identification of the different parameters for first-year students can be based on a selection on observables assumption. Formally, $Y_{it1}\left(1\right), Y_{it1}\left(0\right) \perp D_{it1}|X_{it\tau}$, where $Y_{it\tau}\left(d\right)$ denotes the potential outcome when $D_{it\tau} = d$. In this setting, it is possible to model the relation between the outcome variable and the treatment using different models. For example, one could assume linearity, *i.e.*

$$Y_{it\tau} = \alpha D_{it\tau} + \beta X_{it\tau} + \epsilon_{it\tau} \tag{2}$$

In which case one could use linear methods for the estimation, such as OLS.

However, given the binary nature of the dependent variable, it is also possible to model it in a binary choice framework using a latent variable:

$$\begin{aligned} Y_{it\tau} &= \mathbf{1}\left(Y^*_{it\tau} \geq 0\right) \\ Y^*_{it\tau} &= \alpha D_{it\tau} + \beta X_{it\tau} + \epsilon_{it\tau} \end{aligned} \tag{3}$$

where it is usually assumed that $\epsilon_{it\tau}$ has a known distribution, *e.g.* a normal distribution, so that the estimator would be a probit.

Rather than arguing which of these models is the most appropriate, in this paper we consider several of them, and we select the most appropriate using 10-fold cross validation for the following criterion function:

$$MSE = \sum_{t=1}^{T} \sum_{i=1}^{N_t} \left(y_{it\tau} - \hat{y}_{it\tau}\left(d_{it\tau}, x_{it\tau}\right)\right)^2 \tag{4}$$

where $\hat{y}_{it\tau}\left(d_{it\tau}, x_{it\tau}\right)$ is the estimated probability that student i does not drop out, given the observables $\left(d_{it\tau}, x'_{it\tau}\right)'$.

To be more specific, we consider the following models: OLS, logit, probit, and blocking with regression (Imbens, 2015). Moreover, we consider different combinations of time and university dummies, as well as interactions between the grant and individual characteristics.[2]

Define the probability that student i successfully completes the academic year τ at time t as $P_{it\tau}\left(d_{it\tau}\right) \equiv \mathbb{P}\left(Y_{it\tau} = 1 | D = d_{it\tau}, X = x_{it\tau}\right)$, for $d_{it\tau} = 0, 1$. The following three quantities are relevant for the assessment of the assignment of grants by the policy maker:

$$P_{it\tau}(0) \tag{5}$$

$$P_{it\tau}(1) \tag{6}$$

$$P_{it\tau}(1) - P_{it\tau}(0) \tag{7}$$

Equation 5 denotes the probability that student i successfully completes year τ without

[2] In this current version of the paper, the set of covariates used is predetermined. Future versions of the paper will incorporate the selection of covariates through cross-validation.

a grant. Given the monotonic effect of the grant on this probability, it also represents the probability that awarding the grant on student i would be wasteful, since the student would not need it to continue to the next year. We refer to this as an ineffective grant of type I. Similarly, Equation 6 denotes the probability that student i successfully completes year τ with a grant. As a result, awarding the grant to student i would be also wasteful with probability $1 - P_{it\tau}(1)$, which is the probability that student i would dropout from university regardless of whether he is assigned a grant or not. We refer to this as an ineffective grant of type II. Finally, the difference between these two probabilities (Equation 7) captures the probability that student i completes year τ only if he is awarded a grant. We refer to this as an effective grant.

Knowledge of these probabilities allows the policy maker to allocate grants according to some rules that maximize some social welfare measure. For example, the policy maker could be interested in maximizing the absolute number of successful graduates, a measure that captures the efficiency of the allocation mechanism. On the other hand, the policy maker could be concerned with inequality of outcomes across different subpopulations, such as socio-economic status or gender.

Consequently, the assignment rule can discriminate based on merit or belonging to some subpopulation. In this analysis, we consider the following assignment rules:

1. Effectiveness-based assignment: grants are awarded to those for whom the probability of the grant being effective is highest.

2. Merit-based assignment: grants are awarded to those for whom the probability of dropping-off is lowest.

3. Region-based assignment: funds are distributed amongst regions and grants are awarded to those born in that region for whom the probability of the grant being effective is highest.

4. SES-based assignment: grants are awarded to those with a smaller value of a socio-economic status variable. A similar rule would be based on income, assigning grants to students

whose families have a smaller income than some pre-specified threshold.

5. Gender-based assignment: funds are split into two shares, one for students of each gender, and grants are awarded to those for whom the probability of the grant being effective is highest within each group.

This list is not exhaustive, and several combinations or the former and other assignment rules could be considered. In Section 6 we report several statistics of interest for each rule in this list. In particular, we report the proportion of effective and ineffective grants of each type, the number of dropoffs, and... for the overall population and the following subpopulations: male and female students, high and low SES students,...

5 Results

Table 1 reports the cross-validated MSE of the different estimators. The binary choice estimators consistently have a smaller MSE than the OLS or blocking with regression estimators. Specifically, the probit that interacts the treatment with all covariates and includes university and period effects (specification 6) minimizes the MSE.

Table 1: 10-Fold Cross-Validated Mean Squared Error

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CV-MSE	1368.8	1366.1	1361.2	1360.8	1360.5	1360.2	1364.4	1364.0	1364.7	1364.2
Estimator	OLS	OLS	Logit	Logit	Probit	Probit	BR	BR	BR	BR
TIC		✓		✓		✓		✓		✓
Uni×period FE	✓	✓					✓	✓		
Uni&period FE			✓	✓	✓	✓			✓	✓

Notes: TIC stands for treatment interacted with covariates.

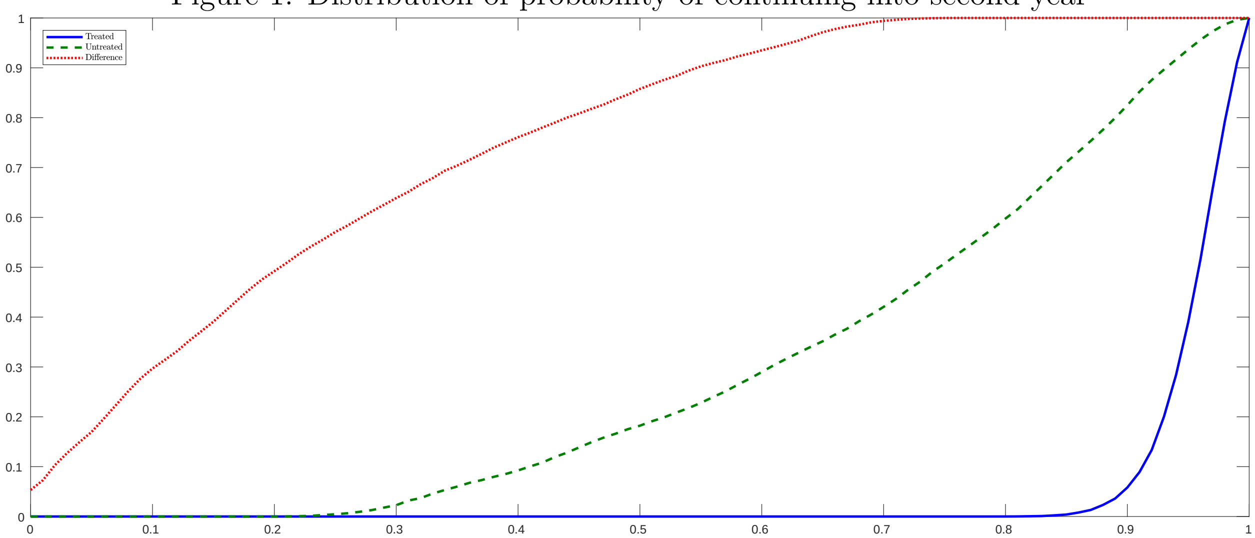
The comparison between being awarded a grant and not is shown in Table 2. It shows the distribution of successfully completing the first year at university when no student and every student is awarded a grant, as well as the distribution of the individual differences. On average, the increase in the probability of graduating equals 24.7%. The difference is however heterogeneous: in particular, over 90% of the students are estimated to benefit from the grant, and for 50.8% of the students this increase is larger than 20 percentage points. These distributions are shown graphically in Figure 1.

Table 2: Probabilities of continuing into second year

	τ					Mean
	0.1	0.25	0.5	0.75	0.9	
NONE	40.9	56.9	74.5	86.8	93.2	70.6
ALL	91.3	93.7	95.9	97.7	98.9	95.4
DIF	1.9	8.0	20.5	39.0	54.7	24.7

Notes: NONE, ALL, and DIF respectively show the distribution of the probability of continuing into the second year at the university when no student was awarded a grant, when all were awarded a grant, and the distribution of the difference between these two probabilities.

Figure 1: Distribution of probability of continuing into second year



6 Assignment of Scholarships

In our data, the number of students with a grant equals 145,965, 71.1% of the sample. Using the estimates from the selected model in Section 5 we estimate the distribution of the probability of successfully finishing the first year at the university when the grants are given to those students who actually obtained them (baseline case) and on the first of the counterfactual scenarios outlined in Section 4. The results, reported in Table 3 and Figure 2, indicate that assigning the scholarships to those students with a higher increase in probability of advancing into the following year reduces the number of expected dropouts from 7.6% to 5.6%, *i.e.* over a quarter of the total number of dropouts. Alternatively, one could obtain the same expected number of dropouts if grants were assigned using this rule to the 115,561 students with the highest gain, *i.e.* reducing the number of treated units by almost 15 percentage points.

Table 3: Counterfactual probabilities of continuing into second year

			τ			Mean
	0.1	0.25	0.5	0.75	0.9	
BL	83.5	89.4	94.3	97.2	98.7	92.4
CF1	89.1	92.4	95.2	97.2	98.6	94.4

Notes: BL and CF1 stand for baseline and counterfactual #1, as described in Section 4.

7 Conclusions and Next Steps

The current analysis will be extended along several dimensions. Regarding the estimates, we will consider a much larger variety of specifications that combine different sets of covariates, interactions between some of these and the treatment status, as well as other estimation methods. Moreover, we will estimate the distributional impact of other counterfactual scenarios, some of which have already been outlined in Section 4, splitting the sample by years. Moreover, we will evaluate the composition of the grant recipients under different assignment rules. Finally, we will study how to extend the analysis beyond the first year of the university.

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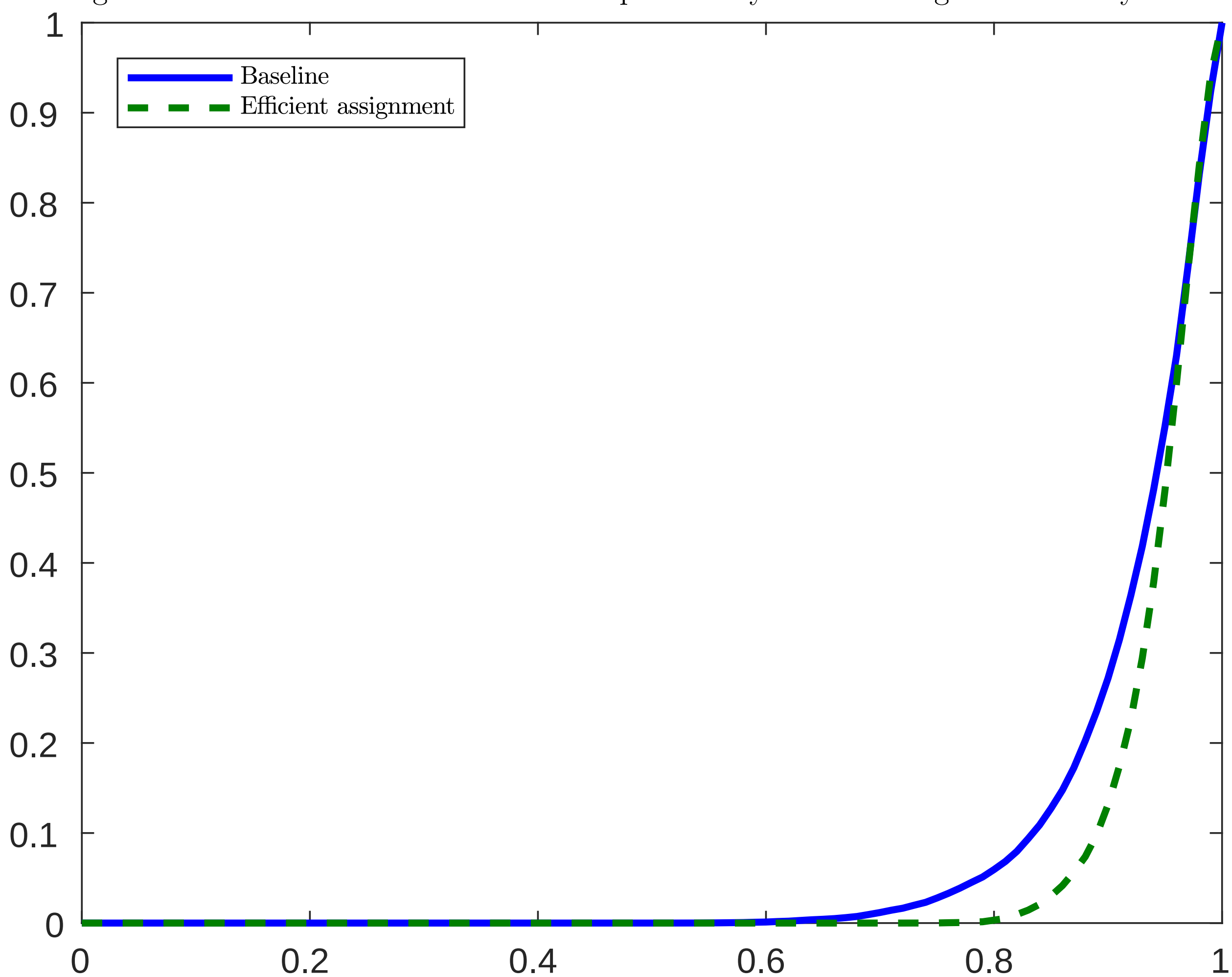
Figure 2: Counterfactual distributions of probability of continuing into second year



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