The role of need-based grants' on higher education achievement *

José Montalbán Castilla †

Paris School of Economics

April 2017

Abstract

Little evidence exists on the specific contribution of performance-based incentive components to the effect of need-based financial aid on student's outcomes. This paper aims at elucidate the causal effect of financial aid on the academic performance of low-income students in higher education, using administrative micro-data from Carlos III University of Madrid. Under the propitious Spanish national means-tested grant program, I am able to disentangle the impacts from two different grant schemes with different intensities of performance-based incentives. I use the sharp discontinuities that are induced by family income thresholds to estimate the effect of being eligible to different categories of scholarships, and exploit the fact that academic performance requirements (i.e., having passed a certain number of credits in the previous academic year) became more stringent for students who applied for a Spanish need-based grant after 2012. I find no effects of the large means-tested grant on students' academic performance with weak achievement component. However, we find positive effects on students' academic performance when the achievement component is more demanding, for those students who are more entitle to the grant. Students' also enhance their fraction of turned-up exams and their average GPA on subjects showed-up to final exam, while no evidence is found on students' subjects selection and dropout effects that might contaminate the results.

Keywords: Need-based grants; college achievement; incentives

JEL Classification: I21, I22, I23, I28, H52

*I would like to specially thank Julien Grenet for his excellent, devoted and generous advise. I am grateful to staff at Universidad Carlos III de Madrid: Paloma Arnaiz Tovar, Gloria del Rey Gutiérrez, Luis Losada Romo and Elena Zamarro Parra for their invaluable help in collecting the data. I would also like to express my gratitude to Andrew Clark, Paul Dutronc, Gabrielle Fack, Martín Fernández, Jesús Gonzalo, Marc Gurgand, Clara Martínez-Toledano, Fanny Landaud , Mariona Segú, and Alessandro Tondini for their useful and wise comments. Finally, I am also grateful to Fundación Ramón Areces for its financial support.

†Paris School of Economics, Boulevard Jourdan, 48, Paris 75014, France. Email: j.montalbancastilla@gmail.com

1 Introduction

Literature focused on the positive college degree premium over individuals' lifetime income is well documented. Access to higher education has considerably grown in the last decades. Over the period 1995 to 2014, the percentage of young adults who enter university in OECD countries has increased from 37 to 59 percent. Despite this general increase in tertiary education admission, students with low-educated parents report substantially lower attainment rates in higher education: of the adults with at least one college-educated parent, 67% attained a tertiary qualification, while adults with low-educated parents only 23% did (OECD (2016)). Success gap rate is driven by both the difficulty to access higher education by low-income students and the fact that their average performance is below their peers of the general population. The larger impediment to enter college education is well reported in the literature (some examples are Ellwood, Kane et al. (2000); Baum, Ma and Payea (2013); Berg (2016)), with main reason pointing out the financial barriers of college education. In addition, evidence that highlights the existence of ability gap between low-income children and their peers, starting in preschool education (Heckman (2006)) and carrying on in adolescence (Cunha and Heckman (2009)), is complemented with papers showing that conditional on being enrolled in higher education, students with low-educated parents generally attain lower grades, take fewer credits, and have higher dropout rates than students with college graduated parents (Terenzini et al. (1996); Lowe and Cook (2003); Pascarella et al. (2004); Sirin (2005); Bowen et al. (2006)).

In order to increase access to post-secondary education for low-income students, many countries provide them with means-tested grants that relieve tuition payment and provide cash transfers to alleviate their budget constraints. Some of these programs embrace the Pell Grant in the US, Maintenance Grant in the UK, *Bourses sur critères sociaux* in France, and *Becas de Carácter General* in Spain. Those plans contain a large amount of college students, accounting about a third in countries as the US and France, and a quarter in Spain.

Literature has mainly focus on the impacts of need-based grants programs on college enrollment (Dynarski (2003); Fack and Grenet (2015); Castleman and Long (2016)), college persistence (Bettinger (2004); Goldrick-Rab et al. (2012)), and earnings (Angrist (1993); Bound and Turner (2002); Stanley (2003)). These papers display the positive influence of those programs on low-income students's outcomes as enrollment, persistence, graduation and earnings, specially on those students who would not have enter university without financial support ("marginal"

students henceforth). Equality of opportunities is reinforced by those schemes raising those students' capacity to access higher education. In addition to the clear necessity of starting college, a crucial part of higher education is academic performance.

Enhance students' achievement might reduce both delays in attainment degree and dropouts, two factors which might be private and socially costly. Grants may affect low-income students' performance by many channels. For instance, the relaxation of financial constraints may prevent students from working when they are at college and induce them to devote more time to study, as well as grant performance-based incentives may increase students motivation to study and self-improve. The importance of boosting students' performance come at stake trough the program cost-effectiveness, reducing time spent in higher education and shortening the performance gap between low-income students and their peers. In addition, as time on tertiary education is highly subsidized by the state, repeated subjects failures and long attainment time rates are costly for taxpayers.

Empirical evidence devoted to clarify the potential impacts of grants on student performance has been developed mainly for merit-based aid, which are allowances conditional on academic achievement. In the first place, those programs were devoted only for top-performer students, whose ability was already high enough and expected payoff from the grant would be negligible. In the 90's, several merit-based programs were introduced for non-top students, as Georgia's Helping Outstanding Pupils Educationally (HOPE), which provided fee waiver for college students who earned at least 3.0 points on high school GPA and whose recipients lost the grant when their university GPA falls below 3.0. Cornwell, Mustard and Sridhar (2006) investigated the effects of the program finding that HOPE scholarship increased freshmen enrollment by 5.9%. Numerous HOPE-style programs have been implemented in different US states as Florida, Georgia or Arkansas. One of the most convincing estimations was provided by Scott-Clayton (2011) evaluation of West Virginia's Providing Real Opportunities for Maximizing In-State Student Excellence (PROMISE) grant, using a regression discontinuity design. The paper shows a positive effect of the grant on students GPAs and credits earned during the first three years of university, only when students faced a minimum GPA requirement to maintain award eligibility, suggesting larger incentive effects of the scholarship than income effects obtained from greater financial aid. Angrist, Lang and Oreopoulos (2009) developed a randomized evaluation with three different treatment groups, offering academic and support services or financial incentives for good grades in a large Canadian university, finding an increase in the academic standing and

grades for women. In addition, Angrist, Oreopoulos and Williams (2014) evaluated the effects of academic achievement awards for college students studying at a Canadian commuter college, which offered linear cash incentives for course grades above 70, detecting positive effects on the number of courses graded above 70 and points earned above 70 for second-year students, but no significant effect on general GPA.

Few papers has been dedicated to explore performance effects on need-based grants. Some examples are: DesJardins and McCall (2007) assessed the impact of the Gates Millennium Scholars Program; Goldrick-Rab et al. (2012) evaluated a random assignment of a private Wisconsin need-based grant; and Brock and Richburg-Hayes (2006) estimated the effects of the Opening Doors program for two New Orleans universities.

Overall, merit-based grants seems to work in favor of performance but with tiny effects, and non-conclusive evidence is found of means-tested grants' positive impact on credit accumulation and GPA. However, those programs exhibit two crucial drawbacks for correctly identify a clean effect in student performance: (i) The majority of means-tested programs schemes display no performance-based requirements or reports weak incentive components. (ii) Most of the literature focus on the extensive effects on enrollment, implying that when there exist an effect on enrollment it is difficult to disentangle the "pure" effect on performance. Furthermore, most of the estimates evaluating the impacts of merit-based and need-based allowances on student achievement are contaminated, due to the fact that the vast majority of papers looked at non-enrolled or freshmen students, who report the highest probability of dropout, specially for marginal students. Then, to my knowledge, intensive effects on performance are not analyzed yet.

The goal of this paper is to test the causal effects of the Spanish national large means-tested grant program with achievement incentive component on students' achievement, usign the full population of undergraduate students' already enrolled in Carlos III University of Madrid (UC3M from now on). I am able to link different administrative micro-data on the universe of students applying for the Spanish national need-based grant program in UC3M over the six academic-year period 2010-2015. I use the sharp discontinuities that are induced by family income thresholds to estimate the effect of being eligible to different categories of allowances. The paper makes several contributions to the literature of student financial aid. First, program's application timing and the fact that students are already enrolled in higher education when they apply for the grant, guarantees estimates on "inframarginal" students (students who would attend university

irrespective of grant award), capturing the intensive margin responses on performance. Second, I exploit the fact that allowance set-up and academic performance requirements (i.e., having passed a certain number of credits and reached a minimum average GPA in the previous academic year) became more stringent for students who applied for the program after 2012, in order to evaluate how the effects changes with different intensities of performance-based incentive component. Third, thanks to the richness of the administrative data, I am able to examine the effects of this reform on a broader set of outcomes (as GPA, dropout, exam attendance or subjects choice) than have been previously considered in the literature.

I find no effects of the different allowance types on students' performance under weak achievement component. In contrast, being eligible to an average of 757 euros grant plus fee waiver under strong performance-incentives, increases students' average GPA in 0.46 points, for those students who are more entitle to the allowance, which corresponds to a raise of about 7.6 percent with respect to the baseline mean. Furthermore, results are persistent during two consecutive years enhancing the cumulative average GPA in two years by 0.39 points per year, corresponding to an increase of about 6.5 percent with respect to the baseline mean. I test the possible mechanisms behind the results showing that neither dropout nor students' subject selection contaminate the estimates. The consistency of effects is proved, displaying an increase in the fraction of students who turn-up to exams, but raising the average GPA on showed-up subjects and average GPA on mandatory subjects, which cannot be selected by the students.

The remainder of this paper is structured as follows. The next section is devoted to explain the Spanish higher education system and the national need-based grant program. Section 3 illustrates which are the data used in the paper and descriptive statistics. Section 4 displays the empirical strategy. Section 5 test the internal validity of the research design, analyze the main results, search for heterogeneous effects, and explore the importance of performance-based incentive component intensity. Section 6 goes into the mechanisms. Section 7 concludes.

2 Background

2.1 Higher Education in Spain

The Spanish educational system is organized as 6 years of primary school (from age 6 to 12), 4 years of secondary education (from age 13 to 16), and two-years of non-compulsory education, which is divided in vocational track (*Ciclos Formativos*) and college preparation (*Bachillerato*).

After graduating from high school, students that agrees on continue their studies may chose between two paths for higher education. The vast majority chose to enroll in college education which offer vocational undergraduate degrees (*CFGS*), academic undergraduate degrees (four-year degree called *Grado*), graduate titles (*Master*) and doctoral studies. Spanish public universities are not selective, given the fact that requirement for entry is to have passed the standard access to university test (*PAU*)[1], which consist on two-year college preparation courses and a standardized entry exam (*Selectividad*) [2]. Outside these tracks, a minority of students enroll in artistic education (arts, music, dance, dramatic arts, etc) which offers undergraduate and graduate degrees.

The cost of higher education in Spain is mainly composed by tuition fees and living expenses. Fee costs vary depending on the Spanish region where the university is located, the academic route selected, and the number of times registered on a concrete subject. Those costs are set at high level, specially in relative terms for low-income students, were the national average tuition fees for a full year in 2015 were 1,100 euros for undergraduate students and between 1,634-2,347 euros for graduate students[3]. Living expenses differ dramatically contingent upon living in a large city or rural area. Given the fact that most of the universities are located in big urban areas, students must incur in relatively high costs. A survey on living conditions of Spanish college students on 2011 exhibit the majority inhabited with their parents, as well as the negligible presence of university residence halls (only 6,3%)[4]. Furthermore, according to current estimations, the average cost of living expenses in Spain for a nine-month period in the first semester of 2015 was 5,069 euros[5], showing the difficulties that students' face to emancipate from their family home and to access higher education, specially for those coming from low-income families. A loan system was in effect in Spain from 2009 to 2011, but the timing – in the midst of a recession – was unpropitious and many students defaulted on their loan payments. The loan system was discontinued as a result [6].

[1] The name has changed from 2017 onward to *Evaluación de Bachillerato para el Acceso a la Universidad* (EBAU). 92% of the students matriculated passed the test in 2015.

[2] The total final grade is composed by a preponderated average with weights 0.6 for *Bachillerato* and 0.4 for *Selectividad*.

[3] *Estadísticas de precios públicos universitarios del MECD* (http://www.mecd.gob.es/educacion-mecd/areas-educacion/universidades/estadisticas-informes/estadisticas/precios-publicos.html).

[4] *Condiciones de vida de los estudiantes universitarios en España. MECD (Eurostudent IV).*

[5] Estimation developed by the *Observatorio de Emancipación del Consejo de la Juventud de España*, based on the rent prices offered by *Idealista.com* and the *Censo de Población y Viviendas de 2011.*

[6] *OECD Skills Strategy Diagnostic Report. Spain. 2015*

2.2 *Becas de Carácter General* Means-tested Grant Program

Becas de Carácter General (BCG henceforth) is the Spanish national financial aid program for low-income students in post-secondary education. BCG is the most ambitious program for higher education students in Spain, since many other allowances exist but this financial aid represents about 86% of the total grants budget. About a quarter of academic undergraduate and 15% of graduate students enrolled received this grant, for a total cost of 829 millions of euros in 2014. The official target of the Ministry of Education is to contribute to the equality of opportunities and improve the educational efficiency by taking advantages of low-income students' potentiality.

The allowances are based on a yearly application process, which eligibility criteria is based on needs requirements, consisting in the annual household income the year before application, and an academic requirement conditional on have passed a certain percentage of subjects on the previous academic year. The program consists on two main levels of grant which are exempt from paying tuition fees: i) Residence Grant (Threshold 1) that focuses on home expenses for students that need to live outside the family home by reason of distance to college; ii) Compensate Grant (Threshold 2) where students' receive cash allowance to compensate the lack of family income. Students who qualify for Residence Grant (RG henceforth) receive an average annual cash allowance of approximately 1,068 euros, and about 2,300 euros for those living outside the family home. When students suit the Compensate Grant (CG from now on) requirements, the average amount increases to 3,000 euros and to 3,500 euros for those who live emancipated from their parents.[7]

The grant structure was changed in the academic course of 2013/2014 affecting students' cash amounts received, scheme design and grant's performance-based incentive component. The previous allowance framework gathered many tiny amount aids (distance to university, educational material, academic performance, etc) in addition to the two main aids described above, but in 2013, these grants broke down into an individual variable component with allowances conceded if the student's family income is below the RG threshold. The student's variable component is endowed with a minimum amount of 60 euros, and it is a function of the student average grade, average grade distribution of the grant holders, applicant's income, and applicants' income dis-

[7] Only fee waiver grant (FW henceforth) with no cash transfers exists. FW grant is extremely close to Threshold 1 (as observed in Figure 1), making non possible to construct two treatment samples which do not overlap. Then, I decided to analyze RG grant separately, due to the higher interest subject to investigate an allowance where students are more entitled to, plus the inclusion of cash transfers. However, as a robustness check I have examined the possible effects of FW grant, with non relevant statistically significant results. Results are available in the online appendix.

tribution[8]. Likewise, more demanding academic performance requirement were required to be grant eligible by raising up the needed fraction of credits passed the year before, and extending the allowance incentive component to previous year average GPA[9]. In addition, average per capita cash allowance amounts decreased for those receiving CG, and for those living outside the family home who received RG. From now onward I will refer as Period I to the three academic year terms of 2010-2012, and Period II to 2013-2015, concerning the two different BCG setups.

2.3 Eligibility Rules

Students are eligible to the BCG grant if they are or have nationality from an European Union county, they are enrolled in a Spanish higher education institution, and do not hold a degree of equal or higher level for the one they are applying for [10]. The qualification for a grant and their different levels depend on the students' household taxable income in the previous year of application, as well as the number of households members[11]. Family income is computed as the addition of the different individual taxable income flows that the households members earned the year before the application, and taxable income is reduced if income sources are coming from any other household member but students' parents, household is classified as large family or family disabled member, among others. The grant is denied not only based on household income, but when household wealth, family business activity and capital returns exceed certain thresholds. Students are able to be allowance holders for a maximum of one year more than the total number of the official program duration of the degree they study, and two years for students who are enrolled in STEM degrees (Science, Technology, Engineering and Mathematics).

Family income thresholds determine students availability to distinct grant levels depending on the number of household members. The fact that income thresholds change with family members create multiple discontinuities, displaying a full set of cutoffs graphically represented by Figure 1. Considering a household with four members, the average sample number of members, applicant

[8]The variable component formula is presented in the online appendix (Figure 10). The Ministry of Education offers an online simulator for the variables amounts in: *http://www.mecd.gob.es/educacion-mecd/mc/becas/2016/estudios-universitarios/simulador.html*

[9]A detailed summary of the academic policy change is provided in papers' online appendix (Table **??**).

[10]From 2013 onward, students from post-obligatory degrees in the educational system are also grant eligible (as college preparation or vocational track). Detailed information about the students' eligibility rules is showed in *Real Decreto 1721/2007 de 21 de diciembre, Boletín Oficial del Estado (BOE)*. Furthermore, each courses application specifics are content in the *BOE*: *Orden EDU/1781/2010 de 29 de junio, EDU/2098/2011 de 21 de julio, Resolución de 2 de agosto de 2012, Resolución de 13 de agosto de 2013, Resolución de 28 de julio de 2014, and Resolución de 30 de julio de 2015.*

[11]The definition of a student's household includes the students' father, mother, siblings smaller than 25 years-old, grandparents, and the applicant. All of them are counted only if they live in the same family dwelling. In case of parental divorce, only the one who live with the applicant is considered.

would not be eligible to the fee waiver grant nor to the RG if household income is higher than 38,831 euros and 36,421 euros respectively, meaning that is approximately placed in the top quintile of income distribution in Spain[12]. The same household would not be able to obtain the highest level of grant, CG, if earned an income above 13,909 euros, which corresponds to the second quintil of Spanish income distribution.

Students must be matriculated in at least 60 ECTS credits, which corresponds to the number of credits in a usual university year[13]. Freshmen students must show an average grade in *PAU* of: (i) 5/10 points (corresponds to have passed the standard access to university exam) in Period I; (ii) 6.5/10 to qualify for all grant levels, and 5.5/10 to be only eligible for FW allowance in Period II. Students who are not in their first year of higher education, must document they passed a certain percentage of credits the year before application:

- *Period I*: 60% if the student is enrolled in a STEM degree, and 80% in any other degrees.
- *Period II*: 65% if the student is enrolled in a STEM degree, and 90% in any other degrees, to be only eligible for the FW endowment. In order to qualify for all grant types, the student must have passed either: (i) 85% if the student attended a STEM degree and 100% for the rest, or (ii) 65% if the student was enrolled in a STEM degree and 90% for the rest, plus have obtained an average GPA of 6/10 or 6.5/10 respectively.

Students are allowed to apply every academic year they wish a grant, starting the application process equally for all applicants. A summary of the application procedure follows:

- *July-early August*: the official call is made public in the Official State Gazette.
- *Mid August-Mid October*: applications are delivered to the Ministry of Education. The application form consist of an online questionnaire. No document transfer is needed since the Ministry contact directly to the institutions concerned: Tax Authority and the University where student is enrolled.
- *December*: applications start to be denied for those students who are not eligible. Application results are not disclose necessarily at the same time for all students, facing each of them a different date. Denied grants are revealed in December, on average, while conceded

[12]Computations based on the *Encuesta Financiera de las Familias 2014*, *Banco de España*.

[13]There exists some exceptions where students' are allowed to be matriculated in less than 60 credits. For instance, when program is composed on less credits per year or when the student is affected by a disability.

allowances are publish after January along the remaining academic year[14]. Usually, the amount allowed is earned approximately one month later of receiving the official answer.

The unique application process of the BCG grant's design allows to estimate the cash allowance effect on student performance with no concerns of dropout effects contaminating the estimates, driven by the marginal students. Students are already enroll at the higher education institution when they apply, and the final result is received as soonest at the end of the first term of the academic course. Hence, estimations are based on the inframarginal students and are founded on intensive margin responses.

A concern for applicants manipulation of information arises for this type of allowances. BCG set-up do not provide room for report false applicants' information since the Ministry directly contact to the Tax Agency and the University in order to check income and academic situation of applicants. Hence, students cannot precisely misreport their true information. Nevertheless, as application implies a decision by the students, it is endogenous. Students might decide to apply only if they are below the income family thresholds, generating a discontinuity in applicants density at the cutoffs. Over 2004-2009, income thresholds changed every year complicating applicant's knowledge of their situation, but over 2010-2015 period, income thresholds remained unchanged. FW grant would be the only one potentially affected by an application sorting, since getting or not the remaining allowances always imply to receive at least the tuition payment, generating no students' incentive for non apply. Moreover, the existence of multiple income reductions changing the individual taxable parental income, complicates applicants' computation of their actual household income counting for the grant, which may encourage them to apply just in case they get it. Manipulation on eligibility threshold is discussed deeply in Section 5.1.

3 Data and Descriptive Statistics

The database used in this paper is a combination of different administrative micro-data of BCG grant applicants' over the six academic-year period 2010-2015, who were enrolled in Carlos III University of Madrid (UC3M henceforth). I exploit the UC3M *SIGMA* database containing four data sources: i) Household, ii) Grant, iii) Access to university, iv) Universe of grades. All databases were matched on the basis of an encrypted student identifier. Household data contains the set of variables that determine grant eligibility (household taxable income, number

[14]Denied grants are disclose on average at the same time for both Period I and II. In contrast, conceded grants was divulged in February-March on average for Period I, and in June for Period II.

of family members, household wealth, family business, large family condition and whether a family members suffers disability), administrative status of scholarship (grant final state, reason of denied and type of scholarship), and principal parent's occupation. Grant enclose details about BCG grant as grant's amounts, concept of each allowance, date of official concession, and the final state. Access to university data-set embrace information about grant applicants when they access university, as gender, nationality, postal code at university entry and score in PAU. Universe of grades data covers all academic curricula of students who at least apply once to BCG from 2004-2015, as degree enrolled, department, subjects matriculated, subject's course, final grade and final call when they obtain the grade.

The yearly average of grant applicants is about 5,300 students. Table 1 displays the number of BCG applicants by year and degree enrolled. The paper estimates are focus on the effects for undergraduate students, which represent 93% of the total applicants, the vast majority. Including graduate students in the analysis would not bring much more statistical power to non-parametric estimates. Likewise, a separated analysis for graduate students would be useless, given the short sample size for the regression discontinuity design and the difficulty to find a reasonable local minimum detectable effect. The study focus on students not rejected from the grant for problems with the Tax Agency nor for exceeded wealth and business boundaries, in order to focus on a sharper regression discontinuity design[15].

Table 2 exhibits some descriptive statistics on the estimation sample of grant applicants. Two treatment samples are constructed: i) RG (Threshold 1) presents applicants who are in the vicinity of the Residence Grant threshold; ii) CG (Threshold 2) displays applicants whose relative household income is close to the Compensate Grant threshold. The table shows that most of the applicants are Spanish, lived in their family dwellings when they entered university, and are enrolled in a non-STEM degree. The average household taxable income is approximately 32,000 euros for RG, but less than half for CG, bringing to light the grant design. Students belong to households with four members on average, which are qualified for large family bonus between 11 to 17 percent of the times depending on the treatment sample. The majority of the family head member worked as blue collar.

[15]Students exclusion would be a problem when rejections by the reasons mentioned above would not be on both sides of the income-eligibility thresholds examined, leading to a sample selection problem. In this paper, this case is not a concern since these rejections are distributed on both sides of the two treatment thresholds.

4 Empirical Strategy

The goal of this paper is to estimate the causal effect of being eligible for a need-based grant on students' performance outcomes under two different grant settings. The estimates of a simple OLS analysis of college achievement on a dummy variable indicating whether the student is eligible for the grant would be biased, even in the presence of determinant observable characteristics as parental income, gender or predetermined ability measures, since the investigation would not account for unobservable characteristics correlated with student performance. In order to estimate the causal effect of being eligible to BCG on student's performance a Regression Discontinuity Design (RDD) is used.

The analysis exploits the sharp discontinuities in the amount of cash allowances conceded. The BCG grant generates two different discontinuities at the RG and CG grant eligible thresholds. Let $E_{i,k,t}$ be a dummy variable that takes value one if applicant i is eligible for a grant of level k ($k = 1, 2$) at year t, and zero otherwise. Eligibility for a level k grant is a deterministic function of the applicant's net household taxable income c_{it} and the number of family members m_{it}:

$$E_{i,k,t} = \mathbb{1}\{c_{it} \leq \bar{c_k}(m_{it})\} \tag{1}$$

where $\mathbb{1}$ is an indicator function and $\bar{c_k}(.)$ is a deterministic function that indicate the household taxable income threshold when the number of family members is m_{it}. Applicant's net parental income, c_{it}, is a function of the gross household taxable income provided by the Tax Agency minus reduction bonuses originated if the household is classified as large family and family disabled member.

The amount of conditional aid A_{it}, conceded to student i at year t is determined as the addition of the different allowances increments α_{ikt} for which students are eligible to the k states of grant:

$$A_{it} = \sum_{k=1}^{2} \alpha_{ikt} E_{i,k,t} \tag{2}$$

The reduced-form equation capturing the connection of the eligibility formula and the outcome variable is the following:

$$Y_{it} = \alpha + \sum_{k=1}^{2} \beta_k E_{i,k,t} + \epsilon_{it} \tag{3}$$

where Y_{it} is the outcome variable of student i at year t and ϵ_{it} are residuals of individual i at time t.

Several identification assumptions are needed in order to identify a causal effect. First, the analysis needs the unconfoundedness assumption (Rosenbaum and Rubin (1983); Imbens (2004)) holds: $Y_{i,t}(0), Y_{i,t}(1) \perp E_{i,k,t} \mid c_{i,t}$. Meaning that conditional on parental income, there is no variation in the treatment status. Usually overlap assumption is needed, but the condition is violated and require extrapolation. To avoid non-trivial extrapolation we focus on the average treatment effect on $c_{i,t} = \bar{c_k}(m_{i,t})$. As values of $Y_{i,t}(0)$ for $c_{i,t} = \bar{c_k}(m_{i,t})$ are not observed by definition, the fact that I observe values of $c_{i,t}$ very close to the threshold is exploited. In order to justify the average treatment effect we need the smoothness assumption (Continuity of Conditional Regression Functions): $E[Y_{i,t}(0) \mid c_{i,t} = c]$ and $E[Y_{i,t}(1) \mid c_{i,t} = c]$ are continuous in c. In other words, I assume that the conditional distribution function is smooth in the forcing variable, and a jump in the conditional probability of outcome at every point of household income is not observed. Then, the conditional distribution function of Y is continuous for all c. Under these assumptions,

$$E[Y_{i,t}(0) \mid c_{i,t} = c] = \lim_{c \downarrow \bar{c_k}(m_{i,t})} E[Y_{i,t}(0) \mid c_{i,t} = c] = \lim_{c \downarrow \bar{c_k}(m_{i,t})} E[Y_{i,t} \mid c_{i,t} = c] \tag{4}$$

Thus, the local average treatment effect of a grant level k is identified as:

$$\beta_k = \lim_{c \uparrow \bar{c_k}(m_{i,t})} E[Y_{i,t} \mid c_{i,t} = c] - \lim_{c \downarrow \bar{c_k}(m_{i,t})} E[Y_{i,t} \mid c_{i,t} = c] \tag{5}$$

Under the assumptions mentioned, the causal effect of being eligible for a level grant k of BCG is identified by comparing outcomes for applicants who are close but above the eligibility income threshold (control group) with students who are near but below (treatment group). A special characteristic of BCG design is the existence of multiple income eligibility thresholds. RG and CG counts with 22 different thresholds (see Figure 1). Due to the negligible statistical power and the problem to identify a reasonable minimum detectable effect by sample size limitations on an exhaustive estimation of all cutoffs, the different thresholds are polled in order to construct two treatment samples: (i) First, a sample polling all the 11 household taxable income cutoffs concerning RG. In this sample, I identify the β_1 treatment effect of being eligible to an approximate average cash allowance of 1,068 euros, for students who already receive the fee waiver. (ii) Second, a sample combining the 11 parental income thresholds of CG. In the

second treatment sample, β_2 treatment effect of being eligible to an approximate average cash allowance of 3,000 euros, for students who already receive the RG quantity.

The treatment effect is estimated using a rectangular kernel suggested by Lee and Lemieux (2010). The bias of this estimator is linear in the bandwidth h, whereas when we non-parametrically estimate a regression function in the interior of the support we typically get a bias of order h^2. The standard errors are computed using standard least squares methods (robust standard errors) clustered at the student level. The bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011). In principle, use a different bandwidth on either side of the cutoff value is possible. However, it is likely that the density of the forcing variable c is similar on both sides of the threshold point. In large samples the optimal binwidth will be similar on both sides. Hence, the benefits of having different binwidths on the two sides may not be sufficient to balance the disadvantage of the additional noise in estimating the optimal value from a smaller sample (Imbens and Lemieux (2008)).

5 Results

5.1 Internal Validity of Empirical Strategy

The internal validity of the RDD depends on the absence of endogenous sample selection in both of the cutoffs sides, meaning that applicants do not sort themselves more frequently in a threshold side than in the other. This behavior would lead to a continuity break in applicants' density at the cutoff, and would imply the treatment group (eligible students) would not be comparable anymore to the control group (non-eligible students). As Imbens and Lemieux (2008) indicate, the present evaluation problem may occur in the common case where the treatment assignment rule is public knowledge, a similar case of the BCG setup.

Examine the non-random sorting of applicants at the cutoffs is key for relying in RDD estimation strategy. McCrary (2008) proposes a test based on an estimator for the discontinuity at the cutoff in the density function of the running variable (family income), which checks the no systematic manipulation of household parental income around the thresholds. Figure 2 shows the graphical representation of the density estimates in the vicinity of the cutoffs, displaying evidence of no density break at the two thresholds examined: RG and CG. As expected, applicants density increases as going down in parental income at Threshold 1, given the fact that more students may think on applying as they are closer to the cutoff. Density estimate at Threshold 2 is constant,

since applicants have incentives to apply in both sides as they would earn fee waiver plus a certain cash amount. Applicants' density is continuous at the cutoffs, ruling out a potential endogenous selection. McCrary test statistics confirm that no statistically significant jump in household income density at the thresholds examined is observed, nor arising sample selection concerns over the two periods studied[16].

An additional key assumption for RDD internal validity is the random sorting of applicants' observable characteristics around the cutoff. Meaning that students' baseline characteristics should be "locally" balance on either side of the thresholds. If some groups of students would sort more frequently on a threshold side but not in the other may indicate sample selection, and it is known in RDD that treatment assignment cannot influence variables determined previously to treatment. In order to test it, RDD local linear regressions are developed for each of the applicants' observable variables as gender, nationality, parental income, PAU score, parents' occupation, etc, as dependent variable. Panel A of Table 3 exhibits the regression results, showing that none of the baseline students' characteristics are unbalance at parental income eligibility thresholds, since all the coefficients are not statistically significant. As suggests, it is also useful to combine the multiple test developed on a single test statistic in order to observe whether all observable variables are jointly non-significantly different from zero. The test is named as seemingly unrelated regression, which estimates a X^2 test. Panel B provides the results of the estimates, showing that the null hypothesis of a jointly balance observable variables is not rejected.

An additional essential inspection must be checked for the internal validity of the research design: testing the first stages. The causal definition of the design is subject to find a statistically significant change in the fraction of applicants awarded a conditional grant and the average cash allowances at the income eligibility thresholds. Figure 3 exhibits the average fraction of applicants awarded with RG and CG grant plotted against the predicted eligibility thresholds. The Figure presents an average of 90 percent of the applicants receiving the grant on both cutoffs. The measure is constructed as an indicator value that takes the value one if the applicant get the grant (understood as getting at least the fee waiver) and zero when grant is denied. Then, a jump on the fraction of grant awarded is not observed given the fact that students above RG eligibility threshold are qualified to the fee waiver grant. The remaining 10 percent of applicants are those who did not complain with grant achievement criteria or had problems with

[16]See online appendix, Table 15

the Tax Agency files. Figure 4 shows the average conditional grant cash amount for all treatment samples applying the strict household income relative distance to the thresholds over the two periods studied. The results indicate a clear increase in the average conditional cash allowance for RG and CG grants over the two periods, reinforced by the statistically significant results of Table 8. RG provides a similar average grant amount for both periods, with an average cash amount of 527 euros in Period I and 757 euros in Period II. CG reports a drastic decrease in the average grant amounts received over the periods, awarding with approximately 2,636 euros in Period I and 1,228 euros in Period II. Thus, a clear discontinuity is observed for both grants in the two period examined. RG grant shows a similar discontinuous average amount for both periods, but different performance-based incentive components. On the other hand, CG presents a bi-dimensional structure with a decrease on the average amount at Period II and different performance-based incentive components in each period.

A concern for an impact in the fraction of re-applicants due to a high time correlation of household income arises. Parental income, at constant prices of 2015, is highly correlated over time. Regressing applicants' income in a given year on students' income the year before leads to a coefficient estimate of 0.73. Despite of the high correlation of income over time, there also exists variation, as the fraction of applicants who reported the same parental income than the one registered the year before is only 3.2 percent. The fact that income-eligibility thresholds are exactly the same amounts since 2010 and the high correlation of income over years, might influence applicants' behavioral responses. Students' who get the grant at a given year might register a higher probability of re-apply the next year than students who did not get it, specially in RG grant which implies a greater entitlement than CG. If happened that re-applicants application rates are larger below the threshold than above, implying a significant jump at the cutoffs, it would suggest that impacts would be driven by this group, which no density break for applicants' at cutoffs but so for re-applicants. Figure 9 plots the average fraction of re-applicants for all treatment samples applying the strict household income relative distance to the thresholds over the two periods studied, displaying no jump on the re-applicants fractions at the cutoffs.

5.2 Impact on Students' Achievement

In order to identify the causal effect of being eligible to BCG grant on students' achievement, I focus on the average GPA, which in Spain is expressed as a measure between 0 and 10 points[17]. However, the effects on several measures of student performance, as fraction of credits passed over the total matriculated, reports the same results.

Figure 5 plots the average GPA for all treatment samples applying the strict household income relative distance to the thresholds over the two periods studied. The solid black lines are the fitted values from a quadratic polynomial approximation. Average GPA means do not highly differ between types of grant, but it does over periods, reporting an average GPA of around 5.8 points in Period I and 6.2 points in Period II. No apparent impact is revealed for CG grant nor in the presence of weak or more demanding performance-based incentive requirements. However, average GPA seems to be affected by RG grant under strong incentives, displaying a clear jump when applicants became eligible at Period II. Table 4 presents the RDD estimates reinforcing the conclusions displayed by the graphical evidence. Being eligible to RG and CG grant do not impact student performance in the presence of weak incentives. In contrast, being eligible to an average amount of 757 euros under strong academic incentives reports a positive impact on the average GPA, with the estimate being significant at the 1 percent level. Local linear regression estimates state that being eligible for a grant increases the average GPA in 0.46 points for those students who are more entitle to the allowance, which corresponds to an increase of about 7.6 percent with respect to the baseline mean.

Baseline estimates are robust over several number of robustness checks performed. The sensitivity of the baseline results is tested by investigating different bandwidth selection criteria, where bandwidth is set to be half and twice as large of the optimal bandwidth proposed by Imbens and Kalyanaraman (2011), and performing the local polynomial regression with robust bias-corrected confidence intervals proposed by Calonico, Cattaneo and Titiunik (2014). Moreover, the baseline results are tested adding several predetermined applicant control variables (as PAU percentile rank, gender, STEM degree, etc) and year fixed effects in order to capture the outcome variable time trends. The results are robust to all different specifications and vary from an effect of 0.27-0.5 average GPA points, which corresponds to about 4.5-8.3 percent with respect to the baseline mean[18]. The estimates precision is sensible due to the limited sample size. However,

[17] GPA equivalence is the following: less than 5 points corresponds to a D grade 5 points to a C grade, 7 points to a B grade, 8 to a B+, 9 to an A, and 10 to a A+.

[18] Table 12 presents the results of each robustness check in online appendix.

the sign and the statistical power of the effects hold over the different specifications providing conviction to believe a robust impact of grant eligibility on students' performance.

Most of the literature focus on the extensive effects on enrollment and mainly on entry students. When an effect on enrollment exists (which is often stronger for freshmen students), it is difficult to disentangle the effect on performance and enrollment. The central advantage for identification of the intensive margin response on students' performance is the special design of the policy that allow to estimate the effects on already enrolled students from all academic courses, which dropout rates are negligible. Nonetheless, it is important to prove that the baseline estimates are not contaminated by dropout effects, which can artificially decrease the average GPA for those applicants above the eligibility thresholds, producing misleading estimates. Table 11 displays the RDD estimates on official dropout for RG and CG by period. Being eligible to RG and CG grant do not impact students' dropout nor in the presence of weak or strong incentives. The results are reassuring the robustness of baseline estimates.

An empirical question arises about the persistence of the effects over time. A natural way to compute them would be comparing students who received the grant for more than a year in a row with the ones that never get the allowance, and whose household income would be in the neighborhood of the thresholds. However, this procedure would lead to bias estimates given the sample selection problem rising by the break in applicants' density and non-comparability of both groups. Nonetheless, I can compute the effect of being eligible to grant allowance on the cumulative average GPA over different years. In other words, conditional on applying for a grant at time t with a certain household income, it is possible to compute the cumulative average GPA over different years for those students. This method would provide unbiased estimates and no sample selection concerns, but potentially the first stage would be decreasing over years due to the different application status of applicants at the successive years, and the distinct household income presented every academic course[19]. Local linear regression estimates reports that being eligible for a grant under strong performance-based incentives increase the cumulative average GPA in two years in 0.39 points per year, for those students who are more entitle to the allowance, which corresponds to an increase of about 6.5 percent with respect to the baseline mean. The results are robust to the inclusion of predetermined applicants variables and time fixed effects, and to set the regression bandwidth to be twice as large of the optimal bandwidth proposed by Imbens and Kalyanaraman (2011),with results varying from 0.23-0.39, which corresponds to a

[19]First stages and sample density are presented in the Online Appendix.

4-6.5 percent with respect to the baseline mean. Nonetheless, results are not robust to set the regression bandwidth to be half as large of the optimal bandwidth nor to the the local polynomial regression with robust bias-corrected confidence intervals proposed by Calonico, Cattaneo and Titiunik (2014). Probably it is given by the difficulty to find a reasonable minimun detectable effect in RDD when sample size do not reach a thousand observations, which is the case when the bandwidth suffers a reduction as the ones imposed by these two robustness criteria.

5.3 Heterogeneous Effects of the Impact on Students' Achievement

Despite of the clear and robust effects of the baseline estimates, investigate the existence of heterogeneous results for different subgroups of population is convenient. I analyze the differential effects of the estimates by gender, predetermined academic ability and residence status, developing separate regressions for each of the groups.

Table 6 displays the results of RDD estimates for RG and CG by period and sample subgroups. Both males and females register positive effects on student performance, but different magnitudes (Panel A). The difference of the coefficient estimates is statistically significant. Males report higher performance effects than females for being eligible to RG grant under strong academic incentives, with almost doubled total and relative effect with respect to their respective baseline means. Panel B explores heterogeneous effects by academic ability. Being eligible to RG grant in Period II has positive impacts on student performance for both students who reports a predetermined academic ability above and below than the median percentile rank in PAU. Students with lower academic ability display larger increments in average GPA, however, the difference is not statistically significant. Panel C exhibits the results for the different applicants' residence conditions. It seems that positive impacts of RG eligibility on students' performance are driven by applicants who lived with their parents in the Region of Madrid (non-movers henceforth) at the time to university entry, while students who lived outside the family home (movers from now on) when they enter higher education are not affected by grant qualification. The grant structure offers a unique setting to explore the differential effects. Figure 7 plots the different average grant allowances receipt by residence condition groups. While students living outside the family home receive positive amounts decreasing in the second period (from 2,500 to 1,600 euros on average), applicants who live with their parents earned a zero amount in the first period and 410 euros on average in the second period. The grant structure allow to consider the first period of non-movers as a placebo test, when this group of applicants did not receive a

positive average amount and incentive effects were weak. A change from zero to a positive cash allowance of 410 euros on average, interacted with strong academic incentive components report a positive impact on student performance of 0.41 points on average (7 percent with respect to the baseline mean). Both receiving a certain cash amount and strong performance-based incentives seem to be crucial for increase student achievement.

5.4 The importance of the incentive component intensity on raising students' performance

A question is raised about which is the role of performance-based incentive components versus receiving a certain cash amount to increase low-income students' achievement. Figure 4 and Figure 5 display the fact that with a similar average cash amount granted, an allowance setting with strong achievement incentive components is propitious for an increase in students' achievement, opposed to an environment with weak incentives. Nevertheless, Figure 7 and Table 6 show that the effect is only driven by non-movers. Those students do not receive cash allowance in Period I, but so in Period II, while the effect is only significant in Period II. Then, effects might be derived only by cash award with no influence of achievement incentives, and main factor pointing out the change in grant distribution of receivers and not the incentives' change. In order to test the policy's efficiency, a deeper inquiry is needed for determine whether impacts are coming just from the cash endowment, performance-incentive components, or a combination of both.

An ideal way to test it would be to count with a positive amount of cash awarded for non-movers at Period I for RG grant, which is not the case. To shed light on this question, I find convenient to reveal the existence of another income eligibility threshold situated in the vicinity of RG cutoff, that has not been exploded yet[20]: the Displacement and Other Needs Grant (DG henceforth). It was a joint threshold working only in Period I which provided students below the cutoff with different cash endowments for displacement to the university, urban transport, academic material or final undergraduate degree project. A student who received DG grant may obtain only one of the different grants mentioned or a combination of them. Table 13 displays the non-parametric estimates of average cash awarded and average GPA at DG cutoff[21]. The increase in average cash allowance at the threshold in Period I is 631 euros, 543 euros for non-movers,

[20] Around a relative distance to RG cutoff of -0.15, showed in Figure 4 and Figure 7.

[21] Figure 8 plots the different average grant allowances receipt at DG grant by residence condition groups.

and 855 euros for movers, with estimates being significant at the 1 percent significance level. However, RDD estimates on average GPA reflects non-statistically significance for any of the sample groups. Results are robust to different treatment sample sizes, to the addition of several predetermined applicant control variables (as PAU percentile rank, gender, STEM degree, etc) and year fixed effects, to set the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) as half and twice of its value, and to perform the local polynomial regression with robust bias-corrected confidence intervals proposed by Calonico, Cattaneo and Titiunik (2014).

This robustness check is useful to analyze the importance of grant's performance-based incentive components. The clear and key advantages of using DG cutoff is twofold. First, DG grant is located just a relative 15 percent distance below RG threshold, which avoids problems of comparability bias between students in the vicinity of these two cutoffs. The sample group of non-movers receive the first significant cash award at DG in Period I, which makes entitlement to the grant comparable to non-movers RG in Period II. Second, all first-stages are highly significant, and non-movers average received amount in Period I at DG is similar to non-movers in Period II at RG. Using non-movers at Period I for DG grant as a robustness check for RG non-movers in Period II is highly convenient due to the fact that offers an scenario where entitlement to the grant, cash allowances and sample are comparable, but performance-incentive components are different in the two periods. Students' performance is not affected in Period I for DG grant, and it is positively impacted in Period II at RG, under approximately same cash allowance amounts. Then, performance-incentive components play a crucial role in enhancing students' achievement. The results suggest that the interaction of cash allowance and strong performance-based incentive components explains the positive impact on student performance.

6 Mechanisms

An effect of grant eligibility on students' performance for grant applicants who are more attached to the allowance under strong incentive components have been proved, nonetheless, the importance for discover the mechanisms running this impact is essential. The goal is to investigate the robustness degree of the observed achievement increments, which translates to analyze whether performance increments came from an actual rise in students' success or by an spurious combination of easier subjects took and showed up more often to exams.

Table 7 shows the results of RDD estimates on different mechanisms for RG and CG by

period. Performance effects might come from an increase in the fraction of turned-up subjects over the total matriculated. Panel A displays the results of this hypothesis, showing that being grant eligible to RG made higher fraction of students showed-up to final exams at Period II. Although the average fraction of turned-up to exams is already very high (92 percent), qualify for RG grant enhances this average on 3.3 percentage points, which corresponds to an increase of about 3.6 percent with respect to the baseline mean. Figure 6 plots different mechanisms for all treatment samples, graphically reinforcing the results of non-parametric estimates.

However, students might appear with higher frequency to final exams, while their performance on them remained unchanged. The fact that students showed up more often may enhance the total average GPA due to the less frequent inclusion of subjects with grade zero (if not turned-up) for the total average GPA computation, without fully meaning their actual subject achievement boosted. In order to test the hypothesis, I examine the discontinuity of average GPA on showed up subjects, targeting to capture the increase in performance over the subjects they actually took. The null hypothesis is rejected at the 5 percent confidence level, signaling the direction towards a real enhance in student performance. Panel B displays that students who were eligible to RG grant raised their average GPA in showed up subjects on 0.24 points, which corresponds to an increase of about 3.7 percent with respect to the baseline mean.

Despite of the evidence presented, a problem to claim a pure impact in performance arises. It is proved that students are performing better on subjects they turned up, even so, applicants may self-select themselves on easier subjects when they are below the income eligibility thresholds, targeting to increase their probability to meet the grant academic criteria for potentially receive it the next year. Then, average students' subject selectivity may be different on both sides of the cutoffs, leading to a positive impact on performance with misleading interpretation, for a potential suspect of an increase due to the easier subjects took. An intuitive measure of subject selection would be to compute the average GPA of a given subject by year, and average by student subjects matriculated. Though, this measure is strongly correlated with applicants' average GPA, specially in the same academic year, leading to endogeneity concerns, plus the fact that average GPA do not necessarily capture the degree of subject selectivity since subjects with higher average GPA may be easier courses graded better. To test this conjecture, I examine the discontinuity on the average subject academic ability of students' matriculated. First, I compute the average academic ability of the students who took a given subject by year, obtaining subject-year dependent variable. Second, I calculate the average academic ability of the subjects

matriculated by a student in a given year. Since relatively better performing students take subjects which are more complicated on average, this measure provides a proxy for subject selectivity. Endogeneity concerns of this variable given by subject-grade-student selection are discarded by choosing a predetermined measure of academic ability. The null hypothesis of allowance qualification effects on average subject selectivity cannot be rejected.

As an additional robustness check in order to test the clearness of achievement effect, I investigate the differential results on the average GPA for mandatory and elective courses. Students must pass a certain number of elective courses which they have to choose from a determined set of subjects which are degree-course specific, and a determined degree-course specific mandatory courses which are compulsory. In case applicants would self-select in easier courses, it is not unreasonable to claim that students would do it in elective courses rather than in mandatory, due to the fact that they are courses where students have room for subject selection. Panel D and E analyze the grant eligibility effects on average GPA for mandatory and elective courses. The results clarify that the effect origin come from an increase on average GPA in mandatory subjects, finding that applicants who were eligible to RG grant raised their average GPA on 0.43 points, which corresponds to an increase of 7 percent with respect to the baseline mean. On the other hand, despite of the higher average GPA on elective courses compared with mandatory, the null hypothesis cannot be rejected.

7 Conclusions

The unique design of the Spanish national means-tested grant program provides a propitious setting to analyze its causal effect on students' performance. Using administrative micro-data of the full population of grant applicants on a Spanish university, I am able to disentangle the impacts from two different grant schemes with different intensities of performance-based incentives. I use a regression discontinuity design for estimating the causal effect of grant eligibility, analyzing the sharp discontinuities induced by family income-eligibility thresholds. I find that the provision of 757 euros on average increases students' achievement (average GPA and fraction of credits passed), for those who are more entitle to the grant under strong performance-based incentives by approximately 4.5 to 8.3 percent. Furthermore, students' also enhance their fraction of turned-up exams and their average GPA on subjects showed-up to the exam, and these estimates are not contaminated by students' subject selection or dropout effects.

This paper points out to the importance of performance-incentive schemes on need-based grants cost-effectiveness. Results are reliable to claim that means-tested allowance design with strong incentive component enhances grant's efficiency. Nevertheless, further research needs to be done in order to identify potential equity effects of such a grant's design change, towards possible effect on low-income students' college dropout. Although equity cost are not problematic for grant applicants as shown in this paper, with the data available is not possible to determine whether college entrants and continuing students could be discouraged to enroll under such strong performance-incentive scheme. Despite the clear effect on student's performance, deep research concerning potential non-applicants' college dropout effects is required to fully conclude that the new setting is cost-effective.

References

Angrist, Joshua D. 1993. "The effect of veterans benefits on education and earnings." *ILR Review*, 46(4): 637–652.

Angrist, Joshua, Daniel Lang, and Philip Oreopoulos. 2009. "Incentives and services for college achievement: Evidence from a randomized trial." *American Economic Journal: Applied Economics*, 1(1): 136–163.

Angrist, Joshua, Philip Oreopoulos, and Tyler Williams. 2014. "When opportunity knocks, who answers? New evidence on college achievement awards." *Journal of Human Resources*, 49(3): 572–610.

Baum, Sandy, Jennifer Ma, and Kathleen Payea. 2013. "Education Pays, 2010: The Benefits of Higher Education for Individuals and Society. Trends in Higher Education Series." *College Board Advocacy & Policy Center.*

Berg, Gary A. 2016. *Low-income students and the perpetuation of inequality: Higher education in America.* Routledge.

Bettinger, Eric. 2004. "How financial aid affects persistence." In *College choices: The economics of where to go, when to go, and how to pay for it.* 207–238. University of Chicago Press.

Bound, John, and Sarah Turner. 2002. "Going to war and going to college: Did World War II and the GI Bill increase educational attainment for returning veterans?" *Journal of labor economics*, 20(4): 784–815.

Bowen, William G, Martin A Kurzweil, Eugene M Tobin, and Susanne C Pichler. 2006. *Equity and excellence in American higher education.* Univ of Virginia Pr.

Brock, Thomas, and Lashawn Richburg-Hayes. 2006. "Paying for Persistence. Early Results of a Louisiana Scholarship Program for Low-Income Parents Attending Community College." *MDRC.*

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik. 2014. "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs." *Econometrica*, 82(6): 2295–2326.

Castleman, Benjamin L, and Bridget Terry Long. 2016. "Looking beyond enrollment: The causal effect of need-based grants on college access, persistence, and graduation." *Journal of Labor Economics*, 34(4): 1023–1073.

Cornwell, Christopher, David B Mustard, and Deepa J Sridhar. 2006. "The enrollment effects of merit-based financial aid: Evidence from Georgia's HOPE program." *Journal of Labor Economics*, 24(4): 761–786.

Cunha, Flavio, and James J Heckman. 2009. "The economics and psychology of inequality and human development." *Journal of the European Economic Association*, 7(2-3): 320–364.

DesJardins, Stephen L, and Brian P McCall. 2007. "The impact of the Gates Millennium Scholars Program on selected outcomes of low-income minority students: A regression discontinuity analysis." *Bill and Melinda Gates Foundation Working Paper.*

Dynarski, Susan M. 2003. "Does aid matter? Measuring the effect of student aid on college attendance and completion." *American Economic Review*, 93: 279–288.

Ellwood, David, Thomas J Kane, et al. 2000. "Who is getting a college education? Family background and the growing gaps in enrollment." *Securing the future: Investing in children from birth to college*, 283–324.

Fack, Gabrielle, and Julien Grenet. 2015. "Improving college access and success for low-income students: Evidence from a large need-based grant program." *American Economic Journal: Applied Economics*, 7(2): 1–34.

Goldrick-Rab, Sara, Douglas N Harris, James Benson, and Robert Kelchen. 2012. "Need-based financial aid and college persistence experimental evidence from Wisconsin." *Institute for Research on Poverty Discussion Paper*, , (1393-11).

Heckman, James J. 2006. "Skill formation and the economics of investing in disadvantaged children." *Science*, 312(5782): 1900–1902.

Imbens, Guido, and Karthik Kalyanaraman. 2011. "Optimal bandwidth choice for the regression discontinuity estimator." *The Review of economic studies*, rdr043.

Imbens, Guido W. 2004. "Nonparametric estimation of average treatment effects under exogeneity: A review." *Review of Economics and Statistics*, 86(1): 4–29.

Imbens, Guido W, and Thomas Lemieux. 2008. "Regression discontinuity designs: A guide to practice." *Journal of econometrics*, 142(2): 615–635.

Lee, David S, and Thomas Lemieux. 2010. "Regression discontinuity designs in economics." *Journal of economic literature*, 48(2): 281–355.

Lowe, Houston, and Anthony Cook. 2003. "Mind the gap: are students prepared for higher education?" *Journal of further and higher education*, 27(1): 53–76.

McCrary, Justin. 2008. "Manipulation of the running variable in the regression discontinuity design: A density test." *Journal of econometrics*, 142(2): 698–714.

OECD. 2016. "Education at a glance 2016." *Editions OECD*.

Pascarella, Ernest T, Christopher T Pierson, Gregory C Wolniak, and Patrick T Terenzini. 2004. "First-generation college students: Additional evidence on college experiences and outcomes." *The Journal of Higher Education*, 75(3): 249–284.

Rosenbaum, Paul R, and Donald B Rubin. 1983. "The central role of the propensity score in observational studies for causal effects." *Biometrika*, 41–55.

Scott-Clayton, Judith. 2011. "On money and motivation a quasi-experimental analysis of financial incentives for college achievement." *Journal of Human Resources*, 46(3): 614–646.

Sirin, Selcuk R. 2005. "Socioeconomic status and academic achievement: A meta-analytic review of research." *Review of educational research*, 75(3): 417–453.

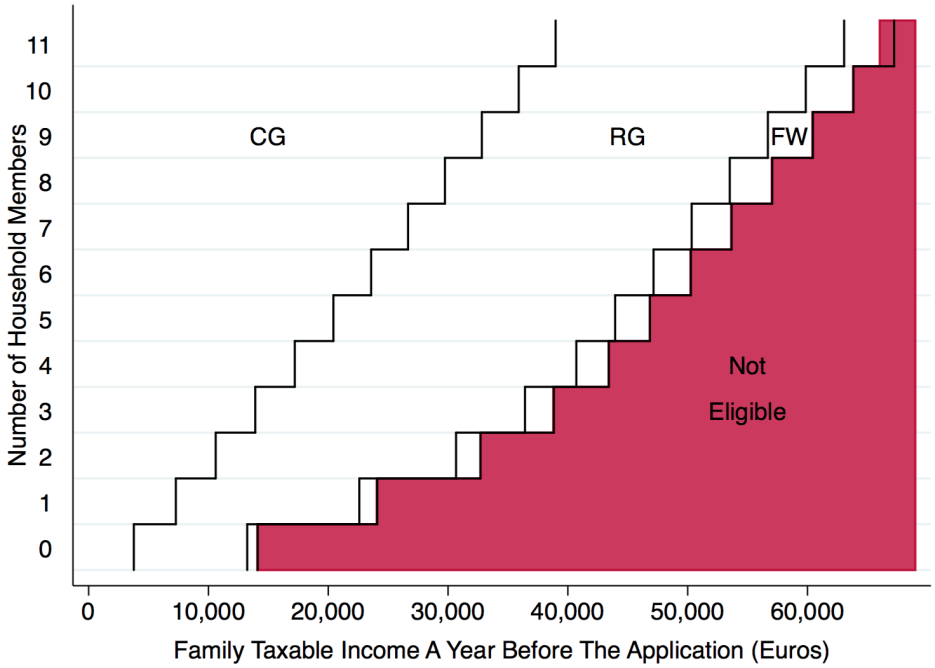
Stanley, Marcus. 2003. "College education and the midcentury GI Bills." *The Quarterly Journal of Economics*, 118(2): 671–708.

Terenzini, Patrick T, Leonard Springer, Patricia M Yaeger, Ernest T Pascarella, and Amaury Nora. 1996. "First-generation college students: Characteristics, experiences, and cognitive development." *Research in Higher education*, 37(1): 1–22.

Appendices

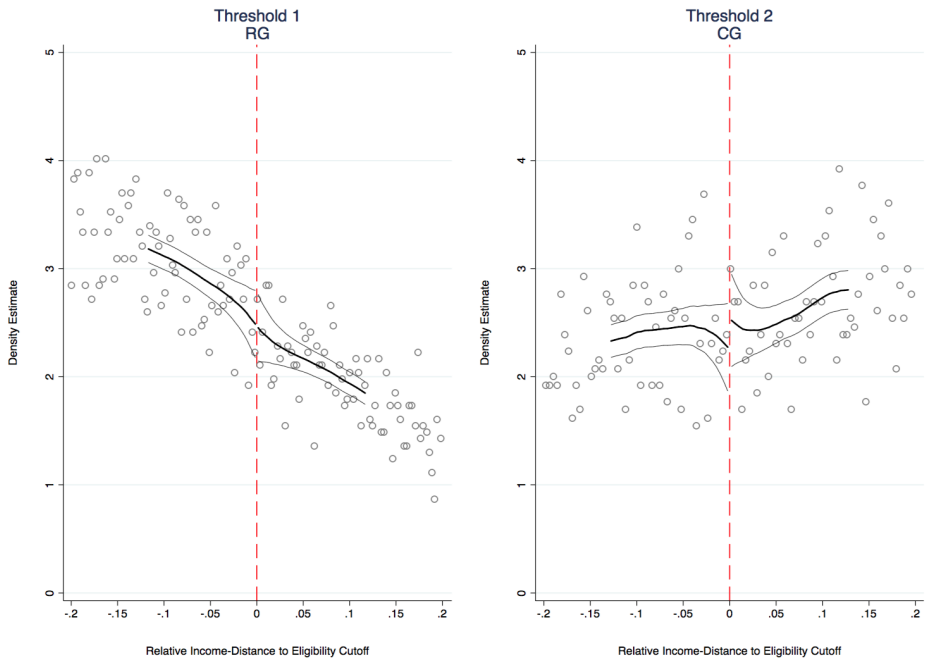
A Main Figures

Figure 1: Setup of Income eligibility thresholds for BCG grant



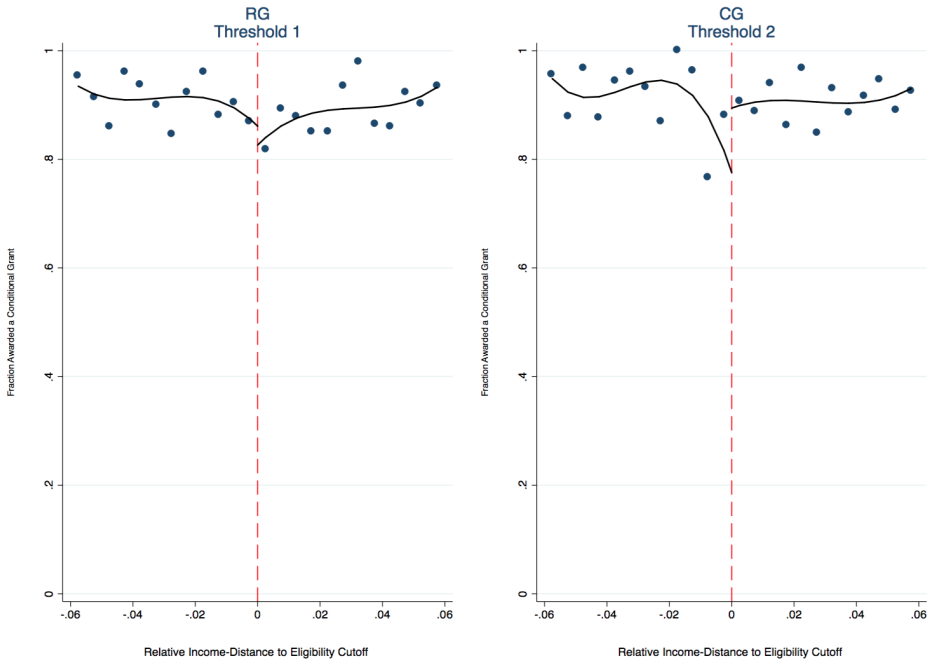
Notes: The figure depicts family income thresholds for different number of household members in the period 2010-2015. Thresholds are exactly the same amounts over the six-year period. FW refers to the fee waiver grant (Threshold 0), RG to Threshold 1 endowment, and CG to Threshold 2 allowance. Thresholds are expressed in 2015 euros.

Figure 2: McCrary (2008) test for 2010-2015



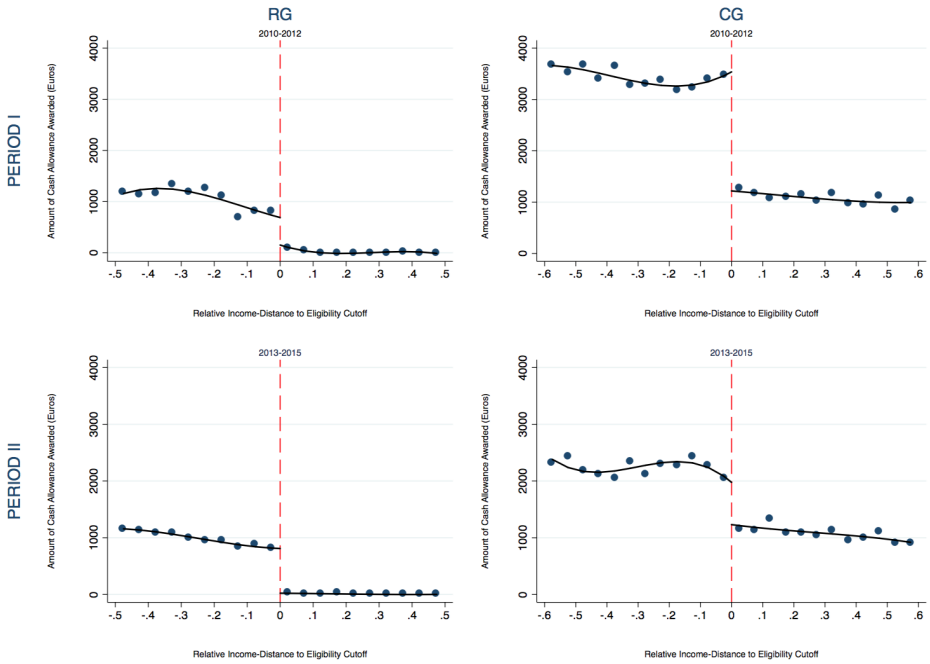
Notes: The figure shows the results of the test proposed by McCrary (2008). The weighted kernel density estimates are plotted, computed separately for each of the sides of the income thresholds RG and CG. The RG treatment sample includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. Optimal bandwidth and bin size are computed by McCrary (2008) selection procedure. "Relative Income-Distance to Eligibility Cutoff" refers to the relative distance of household taxable income to the income eligibility thresholds.

Figure 3: Fraction of Awarded a Conditional Grant for RG and CG (2010-2015).



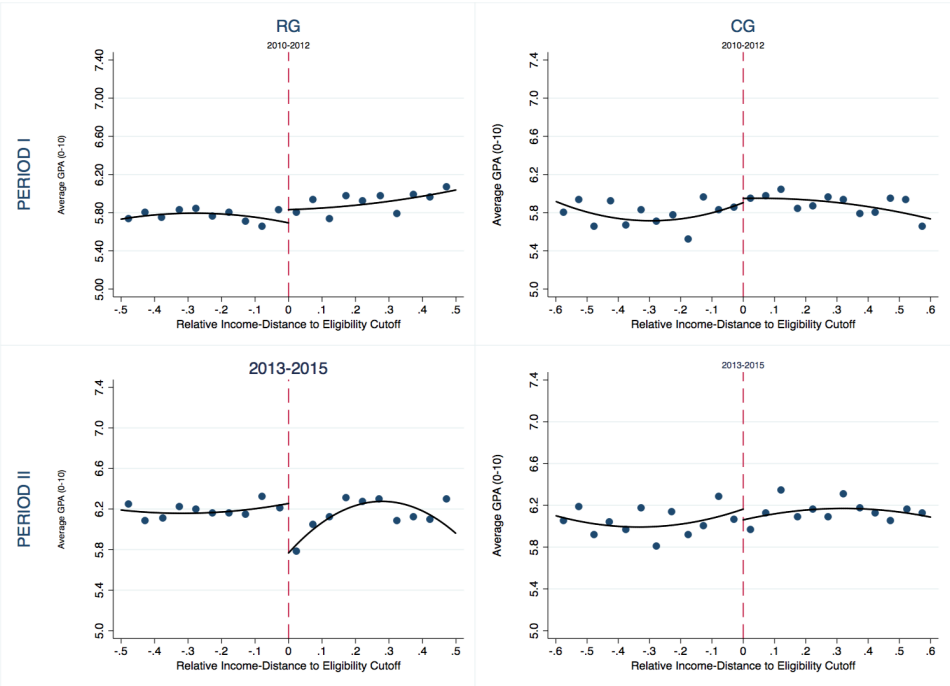
Notes: The dots represent the average fraction of applicants who were awarded a conditional grant per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility Cutoff" refers to the relative distance of household taxable income to the income eligibility thresholds. Red vertical lines identify the income eligibility thresholds.

Figure 4: Average Grant Amounts for RG and CG by period.



Notes: The dots represent the average grant amount per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility Cutoff" refers to the relative distance of household taxable income to the income eligibility thresholds. Red vertical lines identify the income eligibility thresholds.

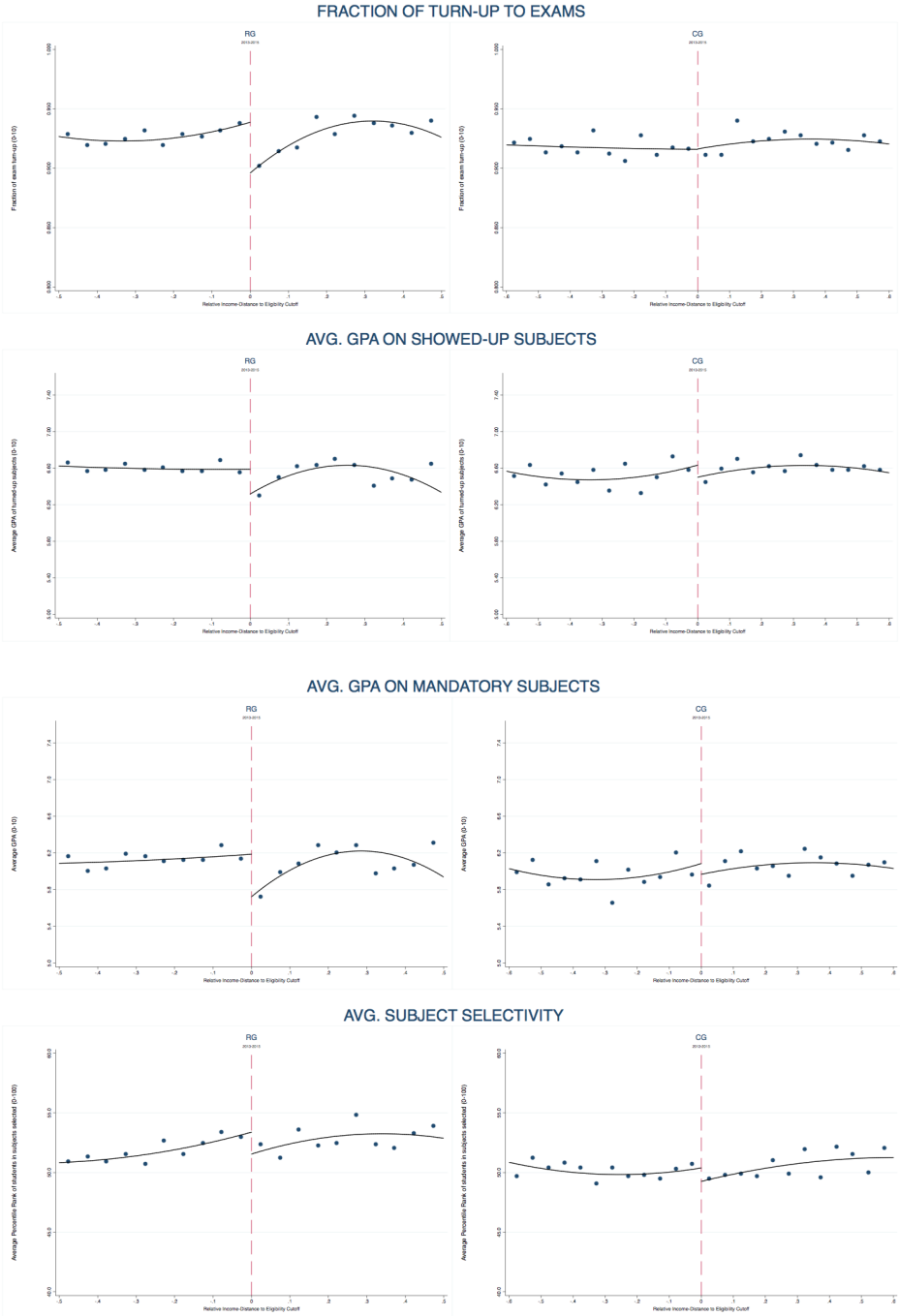
Figure 5: Average GPA (0-10) for RG and CG over Period I and II.



Notes: The dots represent the average GPA per interval of relative income-distance to the eligibility thresholds.

The solid lines are fitted values from a second-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility Cutoff" refers to the relative distance of household taxable income to the income eligibility thresholds. Red vertical lines identify the income eligibility thresholds.

Figure 6: Mechanisms for RG and CG for Period II (2013-2015).



Notes: The dots represent the average fraction of turn-up to exams (first row), average GPA on showed-up subjects (second row), the average GPA on mandatory subjects (third row), and the average subject selectivity (fourth row) per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a second-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility Cutoff" refers to the relative distance of household taxable income to the income eligibility thresholds. Red vertical lines identify the income eligibility thresholds.

B Main Tables

Table 1: Number of BCG applicants (2010-2015).

		Undergraduate Old system	Undergraduate European system	Graduate Programs	Others	**Total**
2010	%	28.78	68.12	3.09	0	100
	N	1,555	3,680	167	0	5,402
2011	%	12.99	82.24	4.76	0	100
	N	701	4,436	257	0	5,497
2012	%	6.11	86.96	6.07	0.86	100
	N	334	4,754	332	47	5,552
2013	%	2.34	90.39	7.03	0.24	100
	N	119	4,602	358	12	5,174
2014	%	0.81	90.26	8.89	0.18	100
	N	41	4,560	449	9	5,128
2015	%	0.04	88.84	10.97	0.17	100
	N	2	4,721	582	9	5,314
Total	%	8.65	84.34	6.76	0.24	100
	N	2745	26,755	2,145	77	31,722

Notes: Total number of BCG applicants to UC3M over the period studied 2010-2015. Undergraduate students studied are the addition of applicants in the old and new system. Undergraduate new system is typically four years degree program, harmonized with the European Union using ECTS credits.

Table 2: Descriptive Statistics on Undergraduate Applicants for Different Treatment Samples (2010-2015).

Treatment sample (Income Eligibility Thresholds)	**RG Threshold 1** (1)	**CG Threshold 2** (2)
Applicants		
Female	0.464	0.473
Spanish	0.983	0.925
Access to University Percentile rank	54.61	51.27
	(28.57)	(28.71)
STEM degree	0.390	0.347
Applications		
Household's taxable income (euros)	31,917	14,211
	(10,036)	(5,700)
# Family members	3.551	3.689
	(0.847)	(0.973)
Disability	0.0132	0.0242
	(0.114)	(0.154)
Large family condition	0.109	0.172
	(0.320)	(0.417)
Live outside the family home	0.278	0.316
	(0.448)	(0.465)
Parental Occupation		
Entrepreneur	0.0439	0.0780
	(0.205)	(0.268)
Blue Collar	0.298	0.435
	(0.457)	(0.496)
Self-Employed	0.0285	0.0779
	(0.167)	(0.268)
Conditional grant		
Awarded a conditional grant	0.674	0.905
Amount of Cash Allowance Awarded (Euros)	678.3	2,093
	(1,035)	(1,800)
Years		
2010	0.153	0.153
2011	0.158	0.157
2012	0.194	0.174
2013	0.165	0.169
2014	0.164	0.169
2015	0.166	0.177
N	10,719	7,448

Notes: The sample is constructed by the administrative database of undergraduate applicants to the BCG grant in Carlos III University over 2010-2015. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. The variable "Live outside the family home" refers to the fraction of applicants who live outside the family home, measured by the student' postal code when they access higher education. The variable "Access to University Percentile Rank" is computed as the percentile rank of the students' academic year high school graduation on the *PAU* grade over the poll of BCG grant applicants from 2004-2015. Household's taxable income is expressed in constant 2015 euros. Standard deviations are in parenthesis.

Table 3: Balance of Baseline Characteristics for Different Treatment Samples (2010-2015).

	RG Threshold 1		CG Threshold 2	
	Baseline mean (1)	Non-parametric Estimates (2)	Baseline mean (3)	Non-parametric Estimates (4)
A. Each baseline charcteristic separately				
Female	0.457	0.022	0.471	0.008
		(0.025)		(0.027)
		9,822		6,892
		[12,812]		[8,971]
Spanish	0.993	0.000	0.949	-0.006
		(0.005)		(0.013)
		4,989		5,641
		[12,812]		[8,971]
Access to University Percentile rank	56.21	1.970	52.54	-0.386
		(1.415)		(1.569)
		10,049		7,173
		[12,812]		[8,971]
STEM degree	0.416	-0.031	0.366	-0.010
		(0.024)		(0.028)
		10,078		5,634
		[12,812]		[8,971]
Households taxable income (euros) (euros)	41,987	107.461	17,408	-72.208
		(296.501)		(233.798)
		7,592		3,402
		[12,812]		[8,971]
Disability	0.0122	0.004	0.0155	-0.004
		(0.005)		(0.008)
		6,849		4,704
		[12,812]		[8,971]
Large family condition	0.129	0.006	0.133	-0.002
		(0.020)		(0.024)
		5,943		4,333
		[12,812]		[8,971]
Live outside the family home	0.296	0.014	0.310	0.008
		(0.023)		(0.024)
		9,677		7,530
		[12,812]		[8,971]
Entrepreneur Parent	0.0399	-0.004	0.0889	0.000
		(0.009)		(0.015)
		7,607		7,069
		[12,812]		[8,971]
Blue Collar Parent	0.222	-0.030	0.423	0.023
		(0.022)		(0.030)
		8,610		4,947
		[12,812]		[8,971]
Self-Employed Parent	0.0202	0.006	0.0706	0.005
		(0.007)		(0.013)
		6,437		8,971
		[12,812]		[8,971]
B. All baseline characteristic jointly: seemingly unrelated regressions				
X2-stat		16.39		5.15
P-value		0.127		0.923

Notes: The table shows the RDD non-parametric estimates for the different applicants' observable variables. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average value of the observable variable above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. The variable "Live outside the family home" refers to the fraction of applicants who live outside the family home, measured by the student' postal code when they access higher education. The variable "Access to University Percentile Rank" is computed as the percentile rank of the students' academic year high school graduation on the PAU grade over the poll of BCG grant applicants from 2004-2015. Household's taxable income is expressed in constant 2015 euros. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Discontinuities in Average GPA (0-10) at RG and CG grants by period

	RG (Threshold 1)			CG (Threshold 2)		
	Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates	Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates
Period I (2010-2012)	527	5.888	-0.1119 (0.119) 4,827 [6,503]	2,636	5.881	-0.1948 (0.153) 2,848 [3,694]
Period II (2013-2015)	757	6.104	0.4627*** (0.141) 3,151 [6,304]	1,228	6.138	0.0450 (0.153) 2,554 [3,910]

Notes: The table shows the RDD non-parametric estimates for the different applicants' Average GPA. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average GPA value above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Discontinuities in Average Accumulated GPA over 2 years for RG and CG grants by period.

	RG (Threshold 1)		CG (Threshold 2)	
	Baseline mean (euros)	Non-parametric Estimates	Baseline mean (euros)	Non-parametric Estimates
Period I (2010-2012)	5.938	-0.0060 (0.113) 4,329 [5,396]	5.940	-0.1549 (0.168) 1,803 [3,02]
Period II (2013-2015)	6.090	0.3929** (0.182) 1,467 [3,417]	6.160	-0.1771 (0.187) 1,248 [2,043]

Notes: The table shows the RDD non-parametric estimates for the different applicants' average grant allowance received. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average grant amount above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Discontinuities in Average GPA (0-10) at RG and CG grants by period and subgroup

		RG (Threshold 1)			CG (Threshold 2)		
		Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates	Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates
A. By Gender							
Females	Period I (2010-2012)	527	6.253	-0.0305 (0.181) 1,703 [3,035]	2,636	6.248	-0.0272 (0.234) 1,065 [1,747]
	Period II (2013-2015)	757	6.517	0.2635* (0.140) 2,895 [2,895]	1,228	6.542	0.1133 (0.173) 1,428 [1,845]
Males	Period I (2010-2012)	527	5.567	-0.1706 (0.192) 1,936 [3,463]	2,636	5.549	-0.1085 (0.209) 1,697 [1,947]
	Period II (2013-2015)	757	5.774	0.4362** (0.177) 2,120 [3,408]	1,228	5.784	-0.0329 (0.235) 1,248 [2,064]
B. By PAU Percentile Rank							
Above Median	Period I (2010-2012)	527	6.301	-0.1541 (0.159) 2,247 [3,588]	2,636	6.356	-0.4134* (0.217) 1,128 [1,932]
	Period II (2013-2015)	757	6.565	0.4249*** (0.156) 2,277 [3,406]	1,228	6.655	-0.0793 (0.198) 1,168 [1,877]
Below Median	Period I (2010-2012)	527	5.333	0.0430 (0.207) 1,434 [2,747]	2,636	5.335	0.0403 (0.233) 1,215 [1,675]
	Period II (2013-2015)	757	5.467	0.5841** (0.239) 992 [2,787]	1,228	5.603	0.0737 (0.242) 1,097 [1,964]
C. By residence condition							
Living with parents	Period I (2010-2012)	527	5.786	-0.0879 (0.162) 2,429 [4,734]	2,636	5.816	-0.1212 (0.186) 1,909 [2,565]
	Period II (2013-2015)	757	5.983	0.4075*** (0.146) 2,952 [4,440]	1,228	6.027	-0.0069 (0.202) 1,509 [2,633]
Living outside the family home	Period I (2010-2012)	527	6.130	0.1160 (0.220) 1,484 [1,764]	2,636	6.045	-0.2770 (0.296) 752 [1,129]
	Period II (2013-2015)	757	6.394	0.1732 (0.236) 1,142 [1,863]	1,228	6.383	0.0076 (0.219) 1,126 [1,276]

Notes: The table shows the RDD non-parametric estimates for the different applicants' variables. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average variable value above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. The variable "Live outside the family home" refers to the fraction of applicants who live outside the family home, measured by the student' postal code when they access higher education. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Discontinuities for the mechanisms variables at RG and CG grants by period

	RG (Threshold 1)			CG (Threshold 2)		
	Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates	Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates
A. Fraction of Turn-up to Exams						
Period I	527	0.911	-0.0003	2,636	0.896	-0.0090
(2010-2012)			(0.012)			(0.013)
			3,325			2,904
			[6,503]			[3,694]
Period II	757	0.924	0.0333***	1,228	0.922	-0.0022
(2013-2015)			(0.010)			(0.013)
			4,098			2,593
			[6,304]			[3,91]
B. Average GPA on Showed-up Subjects						
Period I	527	6.380	-0.0897	2,636	6.462	-0.0492
(2010-2012)			(0.089)			(0.130)
			5,003			2,234
			[6,48]			[3,676]
Period II	757	6.523	0.2420**	1,228	6.595	0.1035
(2013-2015)			(0.108)			(0.130)
			3,213			2,148
			[6,283]			[3,896]
C. Average Subject Selectivity						
Period I	527	52.43	1.5103*	2,636	51.10	0.6439
(2010-2012)			(0.888)			(1.240)
			3,915			1,739
			[6,503]			[3,694]
Period II	757	52.64	1.2108	1,228	50.58	0.8757
(2013-2015)			(0.829)			(1.053)
			5,285			2,622
			[6,304]			[3,91]
D. Average GPA on Mandatory Subjects						
Period I	527	5.847	-0.1131	2,636	5.817	-0.0818
(2010-2012)			(0.129)			(0.174)
			4,075			2,237
			[6,496]			[3,687]
Period II	757	6.054	0.4294***	1,228	6.061	0.0780
(2013-2015)			(0.142)			(0.154)
			3,233			2,683
			[6,298]			[3,908]
E. Average GPA on Elective Subjects						
Period I	527	6.780	0.1168	2,636	6.858	-0.6745**
(2010-2012)			(0.217)			(0.314)
			1,129			598
			[2,305]			[1,421]
Period II	757	7.160	0.4554	1,228	7.220	0.0629
(2013-2015)			(0.325)			(0.282)
			509			459
			[2,075]			[1,427]

Notes: The table shows the RDD non-parametric estimates for the different applicants' Average GPA. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average GPA value above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Online Appendix

C.1 First Stages

Table 8: Discontinuities in Average Allowance Amounts at RG and CG grants by period

	RG (Threshold 1)		CG Threshold 2	
	Baseline mean (euros)	Non-parametric Estimates	Baseline mean (euros)	Non-parametric Estimates
Period I (2010-2012)	23.45	527***	1,275	2,636***
		(80.400)		(140.600)
		3,460		2,334
		[6,503]		[3,694]
Period II (2013-2015)	10.46	757***	1,284	1,228***
		(36.564)		(114.357)
		5,297		2,570
		[6,304]		[3,910]

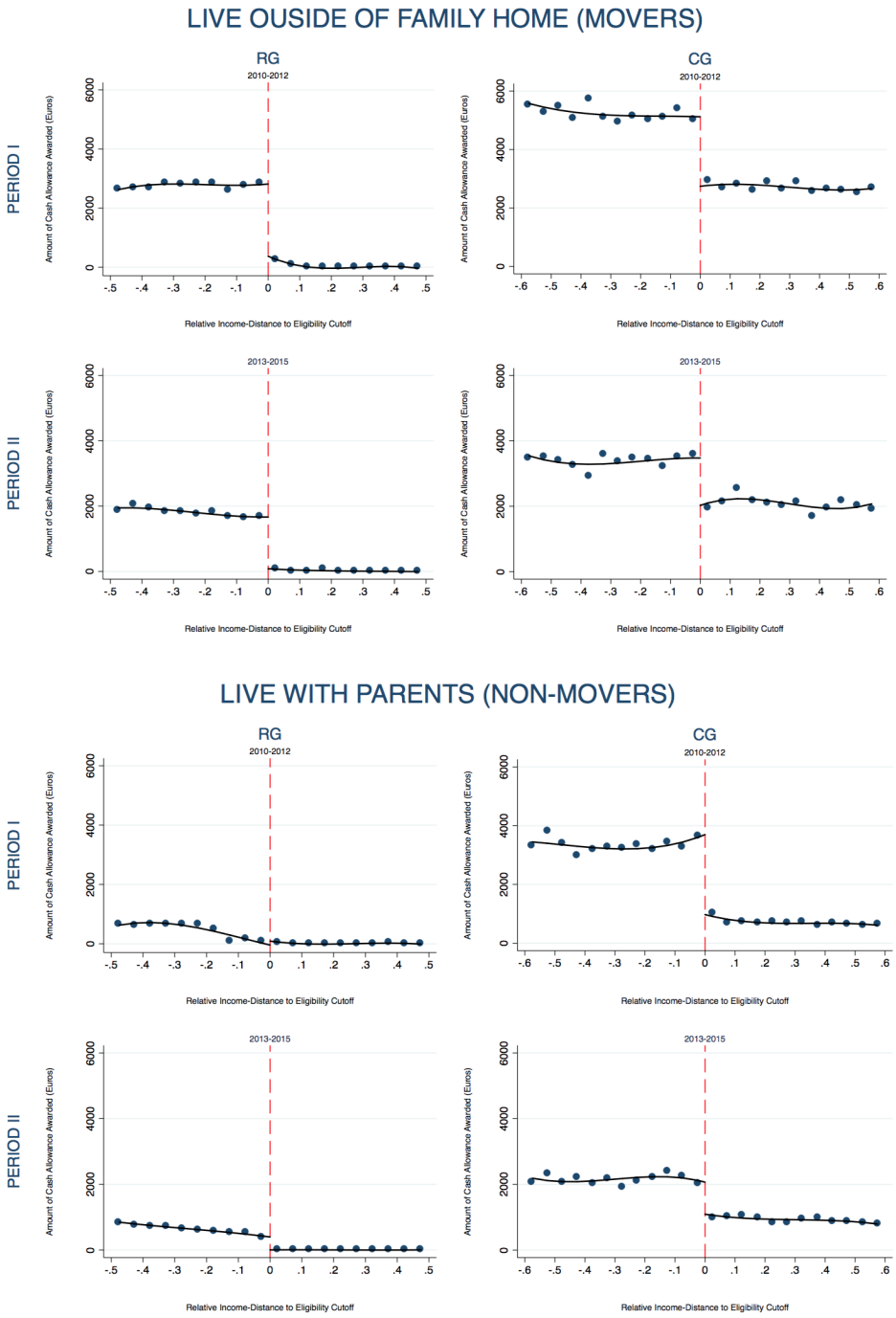
Notes: The table shows the RDD non-parametric estimates for the different applicants' average grant allowance received. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average grant amount above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Average Allowance Amounts at RG and CG grants by period and subgroup sample

		RG (Threshold 1)		CG (Threshold 2)	
		Baseline mean	Non-parametric Estimates	Baseline mean	Non-parametric Estimates
A. By Period total sample					
Total Applicants	Period I (2010-2012)	23.45	527***	1,275	2,636***
			(80.400)		(140.600)
			3,460		2,334
			[6,503]		[3,694]
Total Applicants	Period II (2013-2015)	10.46	757***	1,284	1,228***
			(36.564)		(114.357)
			5,297		2,570
			[6,304]		[3,910]
B. By Gender					
Females	Period I (2010-2012)	19.68	771***	1415	2,871***
			(129.915)		(177.588)
			1,375		1,405
			[3,038]		[1,747]
	Period II (2013-2015)	20.06	889***	1423	1,369***
			(50.654)		(153.887)
			2,895		1,372
			[2,895]		[1,845]
Males	Period I (2010-2012)	26.83	373***	1149	2,411***
			(104.918)		(196.148)
			2,010		1,217
			[3,463]		[1,947]
	Period II (2013-2015)	2.807	607***	1163	1,056***
			(48.102)		(178.574)
			2,747		1,106
			[3,41]		[2,064]
C. By PAU Percentile Rank					
Above Median	Period I (2010-2012)	30.13	709***	1535	2,702***
			(123.193)		(209.847)
			1,864		1,154
			[3,59]		[1,932]
	Period II (2013-2015)	12.48	945***	1645	1,326***
			(58.862)		(148.844)
			2,353		1,329
			[3,408]		[1,877]
Below Median	Period I (2010-2012)	15.06	334***	950.9	2,647***
			(103.518)		(180.143)
			1,213		1,045
			[2,747]		[1,675]
	Period II (2013-2015)	8.097	567***	910.3	1,139***
			(57.810)		(160.209)
			1,283		1,150
			[2,787]		[1,964]
			[3,41]		[2,064]
D. By residence condition					
Living with parents	Period I (2010-2012)	15.18	-89*	702.6	2,646***
			(45.440)		(113.394)
			1,871		1,783
			[4,737]		[2,565]
	Period II (2013-2015)	2.563	410***	922.7	1,058***
			(18.581)		(133.792)
			2,964		1,201
			[4,44]		[2,633]
Living outside the family home	Period I (2010-2012)	42.93	2,514***	2709	2,379***
			(165.451)		(278.403)
			882		583
			[1,764]		[1,129]
	Period II (2013-2015)	29.47	1,582***	2080	1,253***
			(82.508)		(252.899)
			1,317		683
			[1,865]		[1,276]

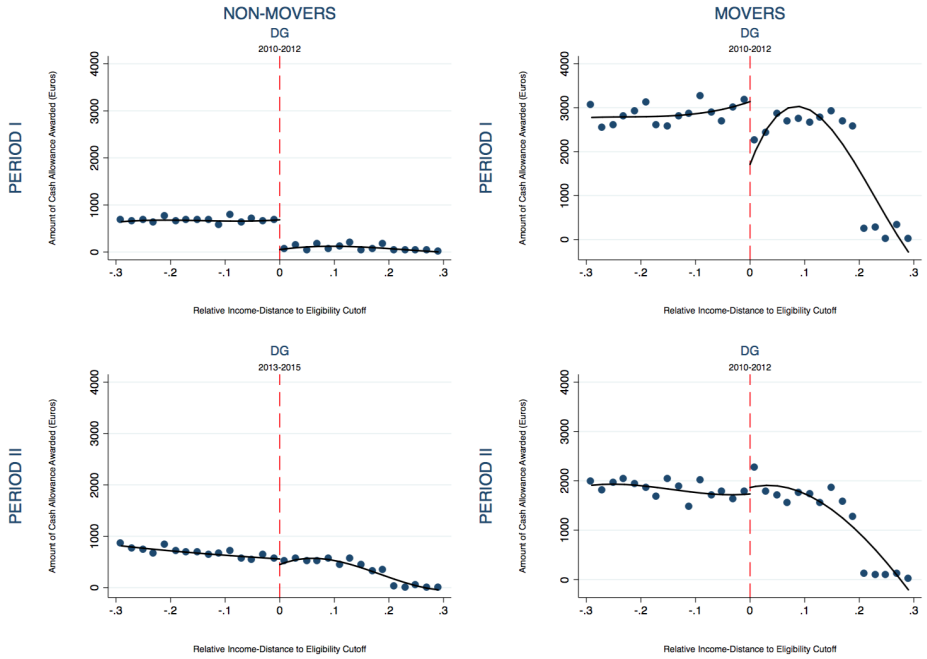
Notes: The table shows the RDD non-parametric estimates for the average allowance amount for different samples. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average variable value above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. The variable "Live outside the family home" refers to the fraction of applicants who live outside the family home, measured by the student' postal code when they access higher education. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 7: Average Grant Amounts for RG and CG by period (Movers vs Non-Movers).



Notes: The dots represent the average grant amount for students who live outside of the family home (first and second row), and students who live with their parents (third and fourth row) per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a second-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility Cutoff" refers to the relative distance of household taxable income to the income eligibility thresholds. Red vertical lines identify the income eligibility thresholds.

Figure 8: Average Grant Amounts for DG by period (Movers vs Non-Movers).



Notes: The dots represent the average grant amount for students who live outside of the family home (first and second row), and students who live with their parents (third and fourth row) per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a second-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility Cutoff" refers to the relative distance of household taxable income to the income eligibility thresholds. Red vertical lines identify the income eligibility thresholds.

Table 10: Discontinuities in Average Allowance Amounts at t+1 for RG and CG grants by period

	RG (Threshold 1)		**CG (Threshold 2)**	
	Baseline mean (euros)	Non-parametric Estimates	Baseline mean (euros)	Non-parametric Estimates
Period I (2010-2012)	206.8	287**	1629	410
		(134.118)		(300.782)
		1,168		801
		[2,054]		[1,174]
Period II (2013-2015)	143.4	336***	1628	367*
		(66.972)		(205.936)
		1,847		878
		[2,108]		[1,25]

Notes: The table shows the RDD non-parametric estimates for the different applicants' average grant allowance received. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average grant amount above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Robustness Checks

Table 11: Discontinuities in Official Dropout from higher education at RG and CG grants by period

	RG (Threshold 1)			CG (Threshold 2)		
	Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates	Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates
A. All applicants						
Period I (2010-2012)	527	0.025	0.0074 (0.012) 2,610 [6,506]	2,636	0.020	-0.0035 (0.009) 2,800 [3,694]
Period II (2013-2015)	757	0.03	-0.0075 (0.011) 4,073 [6,306]	1,228	0.023	0.0181 (0.012) 3,563 [3,910]
B. First year students						
Period I (2010-2012)	527	0.0285	-0.0141 (0.021) 1,363 1902	527	0.0328	-0.0160 (0.019) 518 1009
Period II (2013-2015)	757	0.0417	-0.0201 (0.022) 1,046 1872	757	0.0179	0.0591** (0.028) 824 1138

Notes: The table shows the RDD non-parametric estimates for the different applicants' dropout from higher education. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average dropout above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Robustness Checks: Discontinuities in Average GPA at RG and CG grants by period

	RG (Threshold 1)			CG (Threshold 2)		
	Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates	Avg. Awarded Grant (euros)	Baseline mean	Non-parametric Estimates
A. Baseline Estimates						
Period I	527	5.888	-0.1119	2,636	5.881	-0.1948
(2010-2012)			(0.119)			(0.153)
			4,827			2,848
			[6,503]			[3,694]
Period II	757	6.104	0.4627***	1,228	6.138	0.0450
(2013-2015)			(0.141)			(0.153)
			3,151			2,554
			[6,304]			[3,910]
B. Sensitivity Analysis						
B. 1 Half of the optimal bandwith						
Period I	527	5.888	-0.0985	2,636	5.881	-0.0360
(2010-2012)			(0.162)			(0.215)
			2,471			1,448
			[6,503]			[3,694]
Period II	757	6.104	0.5060***	1,228	6.138	0.1916
(2013-2015)			(0.192)			(0.218)
			1,588			1,357
			[6,304]			[3,91]
B. 2 Twice of the optimal bandwith						
Period I	527	5.888	-0.0611	2,636	5.881	-0.2061
(2010-2012)			(0.105)			(0.135)
			6,503			3,694
			[6,503]			[3,694]
Period II	757	6.104	0.2744***	1,228	6.138	-0.0446
(2013-2015)			(0.106)			(0.123)
			5,990			3,910
			[6,304]			[3,91]
C. RD Robust						
Period I	527	5.888	-0.0373	2,636	5.881	-0.0898
(2010-2012)			(0.197)			(0.271)
			2,129			1,165
			[6,503]			[3,694]
Period II	757	6.104	0.4862**	1,228	6.138	0.1762
(2013-2015)			(0.200)			(0.244)
			1,946			1,342
			[6,304]			[3,91]
D. Baseline estimates with controls						
Period I	527	5.888	-0.1704*	2,636	5.881	-0.1268
(2010-2012)			(0.101)			(0.128)
			4,699			2,776
			[6,503]			[3,694]
Period II	757	6.104	0.2956**	1,228	6.138	-0.0031
(2013-2015)			(0.124)			(0.135)
			3,093			2,506
			[6,304]			[3,91]
E. Placebo test with midpoint between RG and CG						
Period I		5.818	0.1206			
(2010-2012)			(0.157)			
			2,145			
			[4,318]			
		6.168	0.1026			
Period II			(0.137)			
(2013-2015)			2,799			
			[6,369]			

Notes: The table shows the RDD non-parametric estimates for applicants' average GPA. Panel A shows the baseline results estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Panel B displays the estimated treatment effect for half and twice the optimal bandwidth proposed by Imbens and Kalyanaraman (2011). Panel C reports the baseline results estimated performing the local polynomial regression with robust bias-corrected confidence intervals proposed by Calonico, Cattaneo and Titiunik (2014). Panel D exhibits the baseline estimated treatment effect controlling for year fixed effects, PAU percentile rank, STEM degree, whether the student has the Spanish nationality, and dummies equal to one for students who lived outside the family home at the university entrance, female, household disability, household is considered as large family, and if the student's principal tutor is entrepreneur, blue collar or self-employed. Panel E shows a placebo test with a fictitious income eligibility threshold computed as the middle point between RG and CG cutoffs.Baseline mean refers to the average GPA above the eligibility threshold. The RG treatment sample (column 1) includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Discontinuities in Average Awarded Grant and Average GPA at Fee Waiver (FW) and Displacement and other needs grant (DG) by period

		Avg. Awarded Grant (euros) (Threshold 0)		Avg. GPA (0-10) (Threshold 0)	
		Baseline Mean	Non-parametric Estimates	Baseline Mean	Non-parametric Estimates
A. Total sample					
	Period I	0.2	126.6305*	5.848	0.1640
	(2010-2012)		(65.166)		(0.209)
			432		1,262
			[1,868]		[1,868]
	Period II	14	-76.3093	6.182	-0.3253
	(2013-2015)		(47.274)		(0.239)
			448		1,023
			[1,816]		[1,815]

		Avg. Awarded Grant (euros) (Threshold 3)		Avg. GPA (0-10) (Threshold 3)	
		Baseline Mean	Non-parametric Estimates	Baseline Mean	Non-parametric Estimates
A. Total sample					
	Period I	571.7	631***	5.759	0.1254
	(2010-2012)		(129.868)		(0.163)
			1,684		2,381
			[4,254]		[4,252]
	Period II	621.2	-27	6.116	-0.0229
	(2013-2015)		(61.811)		(0.139)
			3,038		3,036
			[4,248]		[4,246]
B. By residence condition					
Living with parents	Period I	85.07	543***	5.660	0.1316
	(2010-2012)		(38.667)		(0.222)
			2,410		1,253
			[3,148]		[3,146]
	Period II	360.5	26	6.012	0.1436
	(2013-2015)		(39.436)		(0.193)
			1,569		1,569
			[2,982]		[2,982]
Living outside the family home	Period I	2015	855***	6.038	0.2744
	(2010-2012)		(290.092)		(0.319)
			399		580
			[1,103]		[1,103]
	Period II	1260	-290*	6.369	0.1247
	(2013-2015)		(147.881)		(0.286)
			716		715
			[1,265]		[1,263]

Notes: The table shows the RDD non-parametric estimates for the average allowance amount received and average GPA for different samples. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2011) for each separated regression. Baseline mean refers to the average variable value above the eligibility threshold. The FW treatment sample includes applicants whose household parental taxable income is within 15 percent of the eligibility thresholds between fee waiver and zero.The DG treatment sample includes applicants whose household parental taxable income is within 30 percent of the eligibility thresholds between fee waiver and Distance and Other Needs allowances. The variable "Live outside the family home" refers to the fraction of applicants who live outside the family home, measured by the student' postal code when they access higher education. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3 RDD Internal Validity

Table 14: McCrary (2008) Test for Manipulation of the Forcing Variable for Different Treatment Samples in DG grant

Treatment sample (Income Eligibility Thresholds)		**FW (Threshold 0)**			
		Log Difference in frequency bins (1)	**Z-stat** (2)	**Bandwidth** (3)	**Bin size** (4)
A. Total sample					
	Period I (2010-2012)	.175 (.193)	.907	.047	.004
	Period II (2013-2015)	.228 (.15)	1.47	.061	.004

Treatment sample (Income Eligibility Thresholds)		**DG (Threshold 3)**			
		Log Difference in frequency bins (1)	**Z-stat** (2)	**Bandwidth** (3)	**Bin size** (4)
A. Total sample					
	Period I (2010-2012)	-.018 (.135)	.14	.071	.004
	Period II (2013-2015)	.119 (.15)	.78	.057	.004
B. By residence condition					
Living with parents	Period I (2010-2012)	-.056 (.166)	.34	.066	.004
	Period II (2013-2015)	.277 (.16)	1.73*	.072	.005
Living outside the family home	Period I (2010-2012)	.051 (.27)	.19	.063	.008
	Period II (2013-2015)	-.476 (.28)	1.70*	.059	.007

Notes: The McCrary test is performed separately for each treatment sample. The FW treatment sample includes applicants whose household parental taxable income is within 30 percent of the eligibility thresholds. The DG treatment sample includes applicants whose household parental taxable income is within 30 percent of the eligibility thresholds. The variable "Live outside the family home" refers to the fraction of applicants who live outside the family home, measured by the student' postal code when they access higher education. Standard deviations are in parenthesis.$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

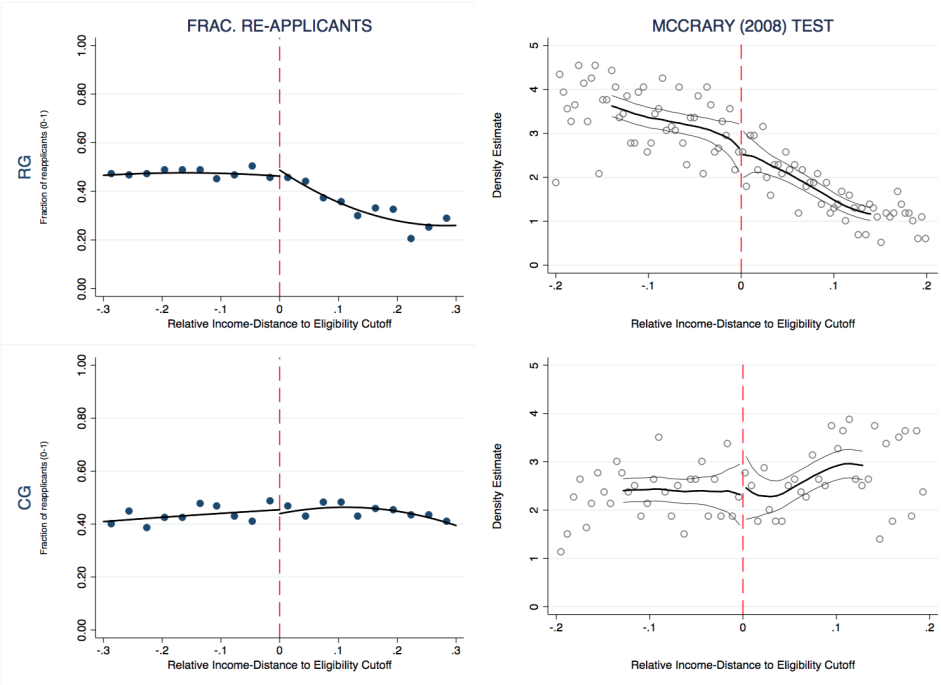
Table 15: McCrary (2008) Test for Manipulation of the Forcing Variable for Different Treatment Samples.

Treatment sample (Income Eligibility Thresholds)		RG (Threshold 1)				CG (Threshold 2)			
		Log Difference in frequency bins (1)	Z-stat (2)	Bandwidth (3)	Bin size (4)	Log Difference in frequency bins (5)	Z-stat (6)	Bandwidth (7)	Bin size (8)
A. By Period									
Total Applicants	Period I (2010-2012)	-.016 (.13)	.12	.079	.004	.188 (.22)	.87	.064	.0064
Total Applicants	Period II (2013-2015)	-.019 (.12)	.16	.10	.004	.147 (.21)	.71	.073	.006
B. By Gender									
Females	Period I (2010-2012)	.002 (.17)	.013	.094	.006	-.285 (.34)	.84	.075	.009
	Period II (2013-2015)	.043 (.21)	.21	.078	.006	.19 (.32)	.59	.061	.009
Males	Period I (2010-2012)	-.125 (.20)	.63	.068	.006	.21 (.25)	.84	.075	.008
	Period II (2013-2015)	-.002 (.17)	.01	.10	.005	.065 (.33)	.2	.062	.008
C. By PAU Percentile Rank									
Above Median	Period I (2010-2012)	-.115 (.19)	.58	.065	.006	-.117 (.25)	.46	.081	.009
	Period II (2013-2015)	-.108 (.18)	.61	.092	.006	.06 (.24)	.25	.10	.008
Below Median	Period I (2010-2012)	.02 (.22)	.11	.063	.006	.28 (.31)	.90	.075	.009
	Period II (2013-2015)	.055 (.21)	.26	.075	.007	.165 (.34)	.49	.069	.009
D. By residence condition									
Living with parents	Period I (2010-2012)	.123 (.15)	.81	.076	.005	.30 (.27)	1.12	.063	.008
	Period II (2013-2015)	.128 (.16)	.78	.079	.005	-.183 (.26)	.70	.071	.007
Living outside the family home	Period I (2010-2012)	-.402 (.33)	1.20	.057	.008	-.289 (.33)	.88	.09	.011
	Period II (2013-2015)	-.258 (.29)	.88	.071	.008	.664 (.36)	1.80*	.072	.01

Notes: The McCrary test is performed separately for each treatment sample. The RG treatment sample includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The CG treatment sample includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. The variable "Live outside the family home" refers to the fraction of applicants who live outside the family home, measured by the student' postal code when they access higher education. The variable "Access to University Percentile Rank" is computed as the percentile rank of the students' academic year high school graduation on the PAU grade over the poll of BCG grant applicants from 2004-2015.. Standard deviations are in parenthesis.$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.4 Re-Applicants

Figure 9: Fraction of re-applicants and McCrary (2008) test for re-applicants density.



Notes: The dots represent the average fraction of re-applicants and density estimates of McCrary (2008) test per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a second-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility Cutoff" refers to the relative distance of household taxable income to the income eligibility thresholds. Red vertical lines identify the income eligibility thresholds.

C.5 Academic Requirements

Table 16: BCG grant academic requirements.

	Fraction of pass credits in the last academic year over 60 ECTS		**Average GPA**		**Grant rights**
	STEM	Humanities and Social Sciences	STEM	Humanities and Social Sciences	
Before 2012	60%	80%	None	None	All
2012 change	65%	90%	None	None	All
2013 onward	85%	100%	None	None	All
	65%	90%	>=6	>=6.5	All
	65%	90%	<6	<=6.5	Only FW

Notes:

Figure 10: Variable component formula.

$$C_j = C_{\min} + \left[\left(C_{total} - S * C_{\min} \right) * \frac{\left(N_j / N_{\max} \right) * \left(1 - \left(\frac{R_j}{R_{\max}} \right) \right)}{\sum_{i=1}^{S} \left(N_i / N_{\max} \right) * \left(1 - \left(\frac{R_i}{R_{\max}} \right) \right)} \right]$$

Notes: Cj= variable component amount that student j receives; Cmin = minimum variable component; Ctotal = total amount of variable componen to distribute among grant's recipients (depend on the year); S= number of applicants who receive variable component; Nj= applicant's average GPA; Ni = average GPA of each applicant to which S refers; Nmax: average GPA obtained by the best decil of the same degree; Rj= applicant's income per capita; Ri = income per capita of each applicant to which S refers; Rmax = maximum income per capita to be awarded with variable component (Threshold 1).