The role of performance incentives in need-based grants for higher education: Evidence from the Spanish *Becas*[*]

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Abstract

There is limited empirical evidence that allows to disentangle the specific contribution of minimum academic standards (from the income effects) to the impact of need-based financial aid on student outcomes. In addition, there is scarce research that is able to isolate the effects of those programs on the intensive margin responses of student performance. This paper investigates the causal effect of financial aid on the academic performance (average GPA and fraction of credits passed) and degree completion of low-income students in higher education. The specific design of the Spanish national need-based grant program allows to disentangle the effect of grant eligibility under different intensities of performance-based incentives and on the intensive margin response on student performance. I use the sharp discontinuities induced by family income thresholds to estimate the effect of being eligible for different categories of allowances, and exploit the fact that academic performance requirements became more stringent for students who applied for a grant after 2012. I find no effects of the grant on student performance under a framework comparable to the weak performance incentives that characterize the typical need-based grant programs around the world. By contrast, I find strong positive effects under a setting with more demanding performance standards. Student's also enhance their final exams attendance rate, their average GPA in final exams taken, and their probability of degree completion. There is neither evidence of an impact of grants on student course selection nor on the probability of dropout from higher education.

Keywords: Need-based grants; performance incentives; college achievement

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

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1 Introduction

The existing empirical evidence suggests strong college degree premium on individuals' lifetime income.[1] Despite the considerable general increase in access to higher education over the last decades,[2] students with low-educated parents report substantially lower attainment rates (OECD, 2016).[3] This gap is driven both by their difficulty to access higher education, mainly due to financial barriers, and by the fact that their average performance is below that of their peers.[4] To relax low-income students' budget constraints, financial aid is provided conditional on meeting several need-based criteria and minimum performance-based standards (i.e. having passed a certain number of credits and/or having earned a minimum average GPA). The literature on financial aid shows positive effects on several students' outcomes, capturing the joint income and incentive effect of grants (i.e. the complementarity between the awarded cash amounts and performance-based standards). However, there is a particular lack of empirical evidence disentangling the specific contribution of performance-based incentives on student performance in the national large scale need-based grant programs.

In this paper, I test the effect of the Spanish national large-scale need-based grant program on student performance and degree completion. Specifically, I investigate whether the intensity of performance-based components alone matters for student achievement. In a nutshell, I find no effects under a setting comparable to the weak performance incentives that characterize the typical need-based grant programs around the world. By contrast, I find strong positive effects on student performance and degree completion under a setting with more demanding incentive components.

To increase access to post-secondary education for low-income students, many countries provide need-based grants that typically cover tuition fees and award cash transfers to alleviate students' budget constraints. Examples of such programs are the Pell Grant in the US, the Maintenance Grant in the UK, the *Bourses sur critères sociaux* in France, or the *Becas de*

[1]See, e.g., Kane and Rouse (1995).

[2]Over the period 1995 to 2014, the percentage of young adults who enter university increased from 37 to 59 percent on average among OECD countries.

[3]Of the adults with at least one college-educated parent, 67 percent attained a tertiary qualification, compared to only 23 percent among those with low-educated parents.

[4]The main deterrent to enter college education has been found to be financial barriers (Ellwood, Kane et al., 2000; Baum, Ma and Payea, 2013; Berg, 2016). In addition, evidence that highlights the existence of an 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).

Carácter General in Spain. Those plans benefit a large number of college students, around one third in the US and France, and one quarter in Spain. In addition to the need-based criteria, most of the programs request applicants to meet minimum performance-based standards. In the US, such academic criteria are the Satisfactory Academic Progress (SAP) requirements for federal need-based aid programs, which generally require students to maintain a cumulative grade point average (GPA) of 2.0 or higher and to complete at least two thirds of the course credits that they attempt.

A particularly difficult and controversial debate is at stake, specially in the US, on whether academic incentives ought to be incorporated (and if so under which form) to the national large-scale need-based grant programs. While some academics and policymakers have supported the idea, others have alerted on whether need-based grant programs attached to academic incentives would lead low-income students to disadvantage situations. Dynarski and Scott-Clayton (2013) claim that "grants that link financial aid to academic achievement appear to boost college outcomes more than do grants with no strings attached". However, the precise role that performance standards tied to grant aid plays on aid effectiveness is not yet clear, due to the limited available empirical evidence disentangling their specific contribution.

This paper aims at brings new evidence on this central issue using a large-scale national need-based grant program. Based on linked administrative micro-data covering the universe of students applying for the Spanish national need-based grant program at Carlos III University of Madrid over the six academic-year period 2010–2015, I exploit the sharp discontinuities induced by family income thresholds to estimate the effect of being eligible for different categories of allowances and performance standards on applicants' outcomes.

This paper makes several contributions to the literature on student financial aid. First, I exploit the fact that grant setting and academic performance requirements became more stringent for students who applied for a need-based grant after 2012, in order to test whether the effect of the grant is affected by the intensity of academic standards. The unique design of the policy allows me to disentangle the grant effects under two different settings of performance standards, holding income effects almost constant. Second, the timing of grant applications in Spain and the fact that students are already enrolled in higher education when they apply for the grant, allow to isolate the effects of grants on the intensive margin responses on student performance, since the extensive margin responses (college enrollment) are essentially muted due to the timing of grant applications. 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 (e.g. GPA, dropout, final exam attendance or selection on courses) than have been previously considered in the literature.

I find no effects of large discontinuous changes in grant amounts at the eligibility cutoff on student performance in the period during which performance requirements were relatively weak and comparable to those found in other need-based grant programs around the world, e.g. the SAP requirement for the renewal of the Pell Grant. By contrast, I find that being eligible for an average of 760 euros grant (relatively to being eligible for only fee waiver) in the period when performance requirements were made more stringent, increases student average GPA and and fraction of credits passed by 0.46 points (on a 0 to 10 scale) and 4.5 percentage points, which corresponds to an increase of approximately 7.6 and 6 percent with respect to the baseline mean. Furthermore, results are found to persist over time, enhancing the student cumulative average GPA over two consecutive years. I investigate the possible mechanisms behind the results showing that neither dropout nor student selection on courses can explain the grant's positive effects on performance. Instead, I find that the effects are driven both by students attending more often to final exams, and by students earning a higher GPA on the final exams taken, including those courses which are compulsory, and hence cannot be avoided by students. In addition, I find positive effects on student's probability of degree completion.

One of the most prominent study in this literature and the closest to this paper is Scott-Clayton (2011), which evaluates the West Virginia's PROMISE grant using a regression discontinuity design. The paper shows positive effects on student 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. On the other hand, Scott-Clayton and Schudde (2016) explore the consequences of SAP failure, finding negative impacts on persistence but positive effects on grades for students who remain in college. A recurrent potential limitation of related papers is the potential endogenous selection around the eligibility cutoffs, which may bias the results.[5] Together with these papers, the Manpower Demonstration Research Corporation (MDRC) has performed several randomized evaluations,[6] as well as Angrist, Lang and Oreopoulos (2009) and Angrist, Oreopoulos and Williams (2014), offering financial incentives for good grades. These

[5] Lindo, Sanders and Oreopoulos (2010), Schudde and Scott-Clayton (2016), Scott-Clayton and Schudde (2016), and Casey et al. (2015) all find similar concerns at the eligibility cutoff, implementing "donut-RD" designs.

[6] See, e.g. Barrow et al. (2014), Cha and Patel (2010), Miller et al. (2011) or Richburg-Hayes, Sommo and Welbeck (2011).

papers point out the importance of performance-based incentives on student performance. In contrast, they cannot entirely disentangle the specific contributions of income and incentive effects, they are narrowly defined programs devoted to specific groups and/or operating at a particular state or university, and often include additional components (such as academic and support services) that make difficult to isolate the specific role of performance standards.

The previous empirical literature exhibits two crucial identification challenges. The first difficulty is to identify incentive effects. Several need-based grant programs report performance requirements for renewal, but it is still not entirely clear which is the relevance of those standards in explaining the effects on student performance. The empirical evidence has found that incentives matter for enhancing student performance, but the majority of need-based programs schemes do not allow for disentangle between income and incentive effects. Second, identifying the effect of need-based grants on student performance when they affect college enrollment is not straightforward. Most of the literature focuses on the extensive margin effects on enrollment, implying that when there exists an impact on enrollment is challenging to disentangle the intensive margin effect on performance. Furthermore, the vast majority of papers looking at the impacts of merit-based and need-based allowances on student achievement may not be entirely representative to all population of college students, due to the fact that they focus on non-enrolled or freshmen students, who report the highest probability of dropout.

Financial aid may influence low-income students' outcomes through two main channels: cost-of-college and incentive effects. First, the relaxation of budget constraints may prevent financially constrained students from working part-time, inducing them to devote more time to study. Second, if students lack of sufficient motivation, have high time preferences, or are not aware of the exact returns to schooling, performance-based incentives may increase their motivation to exert higher academic effort and self-improve. Nevertheless, Fryer (2011) remarks that financial incentives may have two additional effects that work in the opposite direction. First, incentives will have little impact if students lack the structural resources or knowledge to convert effort into a measurable achievement or if the production function has important complementarities out of their control (e.g. effective teachers, engaged parents or social interactions). Second, some argue that financial rewards for students (or any kind of external reward or incentive) will undermine intrinsic motivation and lead to negative outcomes. The main theoretical models of this literature are Manski (1989) "schooling as experimentation" model, and Bénabou and Tirole (2002) model of student behavior under performance standards. In addition, Scott-Clayton and Schudde (2016) propose the most connected model to a context of need-based grants with performance standards and three periods: an evaluation period, a warning period, and an enforcement period. Their theoretical results show that discouragement (dropout) effects will be concentrated among those in the lower part of the ability distribution, while the encouragement (improved GPA) effects should be concentrated among those who are close to the performance requirement threshold. They conclude that a minimum standard is desirable, but determining whether the standard is too high or too low would require weighting the value of encouragement and discouragement effects.

These papers suggest that academic standards might increase the efficiency of aid expenditures by reducing time spent in higher education and improving student performance, but they could also intensify inequalities by inducing low-income students to dropout. As time spent in tertiary education is highly subsidized by the state, performance standards may reduce costs for taxpayers on repeated subjects failures and long attainment time rates, but at the same time, dropout might be private and socially costly.

Related to this paper is the literature on the effects of financial aid. The empirical evidence has mainly focused on the effects 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). Existing studies have documented the positive influence of such programs on low-income students' enrollment, persistence, graduation and earnings, for the sub-population of students who would not have entered university without financial support ("marginal" students). Hence, the available evidence suggests that need-based grants are effective in expanding higher education opportunities for low-income students, raising those students' capacity to access higher education. In spite of the fair amount of research documenting the effects of these grants on college entrance, there is far less evidence on the incentive effects of such programs. Empirical evidence devoted to clarify the potential impacts of grants on student performance has been developed mainly in the context of merit-based aid, which is granted conditional on academic achievement. Generally, these grants have been found to exert positive but small effects on student performance. In the first place, those programs, such as the US National Merit program and Canadian Excellence Awards, were targeted only at top-performers. In the 1990's, several merit-based grants were introduced for non-top students, such as Georgia's Helping Outstanding Pupils Educationally (HOPE), which provided fee waiver for college students who maintain at least an average of B. Numerous HOPE-style programs have been implemented in different US states as Florida or Arkansas, finding positive results for key students' outcomes.[7] Few papers have explored performance effects of need-based grants, with evidence mostly coming from programs devoted to specific groups of population in a particular state or university (see, e.g Goldrick-Rab et al., 2012 for a random assignment of a private Wisconsin need-based grant or Brock and Richburg-Hayes, 2006 for an evaluation of the Opening Doors program for two New Orleans universities), where overall, there is non-conclusive evidence of a positive impact of need-based grants on credit accumulation and GPA.

The remainder of this paper is structured as follows. Section 2 provides institutional background on the Spanish higher education system and on the national need-based grant program. Section 3 describes the data used in the paper. Section 4 explains the empirical strategy. Section 5 discusses the internal validity of the research design, analyzes the main results, explores heterogeneous effects and examines the different mechanisms that could explain the results. Section 6 concludes with a discussion.

2 Institutional Background

2.1 Higher Education in Spain

The Spanish educational system is organized as six years of primary schooling (from the age of 6 to the age of 12), four years of secondary education (from the age of 13 to the age of 16), and two years of non-compulsory education, which is divided into a vocational track (*Ciclos Formativos*) and an academic track (*Bachillerato*). After graduating from high school, students choose whether to pursue into higher education. The vast majority decide to enroll in college education, leading to vocational undergraduate degrees (*CFGS*), academic undergraduate degrees (four-year degree called *Grado*), graduate degrees (*Master*) and doctoral studies. To access higher education, students must pass the standard access to university test (*PAU*),[8] which consist on two-year college preparation courses and a standardized entry exam (*Selectividad*).[9] Spanish public universities accept all students who apply to their programs. If the demand for a

[7] See, e.g. Cornwell, Mustard and Sridhar (2006) for an evaluation of Georgia's HOPE program, Dynarski (2008) and Sjoquist and Winters (2012) for an investigation of Georgia and Arkansas HOPE-like programs, and Castleman (2014) for an analysis of the Florida Bright Futures Scholarship.

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

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

specific program exceeds the number of available seats, students are admitted in the order of their *PAU* grades until all seats are filled. Outside of these two main 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. Tuition costs vary depending on the region where the university is located, the degree program undertaken, and the number of times registered in the same subject. These costs are set at relatively high level, especially in relative terms for low-income students, as the national average tuition fees for a full year was 1,100 euros for undergraduate students in 2015 and between 1,634 and 2,347 euros for graduate students.[10] Given the fact that most of the universities are located in large urban areas, students face relatively high living costs. In 2011, a survey on living conditions of Spanish college students indicated that the majority were living with their parents, and that only 6.3 percent were living in university residence halls.[11] Furthermore, according to current estimations of the first semester of 2015, the average cost of living expenses in Spain for a nine-month period was 5,069 euros,[12] which represent a significant financial barrier to emancipate from their family home and to access higher education. A loan system was functioning 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.[13]

2.2 *The Becas de Carácter General* Need-Based Grant Program

Grant Program. The *Becas de Carácter General* (BCG hereafter) is the Spanish national financial aid program for low-income students in post-secondary education. BCG is the most ambitious program for college students in Spain, since it represents about 86 percent of the total budget for grants in higher education. About a quarter of the academic undergraduates and 15 percent of graduate students enrolled received this grant in 2014, for a total cost of 829 millions of euros. The official objectives assigned to this grant program by the Ministry of Education is to contribute to the equality of opportunities and to improve the educational efficiency by promoting low-income students' potentiality.

The program consists on three main levels of grant: (i) the Fee Waiver (Threshold 0) exempts

[10] Public prices are detailed in *Estadísticas de precios públicos universitarios del MECD*.
[11] See Ariño (2011).
[12] These estimates are based on the CJE (2015), using the rent prices offered by *Idealista.com* and the *Censo de Población y Viviendas de 2011*.
[13] See OECD (2015).

eligible applicants from paying tuition fees; (ii) the Residence Grant (Threshold 1) provides cash allowance which is intended to cover home expenses of students who live away from their family home by reasons of college distance; and (iii) the Compensate Grant (Threshold 2) provides cash allowance to compensate the student's lack of family income. Students who qualify for the Residence Grant (RG grant hereafter) receive an average annual cash allowance of approximately 1,068 euros (or about 2,300 euros) for those living inside (outside) the family home. When students fulfill the Compensate Grant (CG grant hereafter) requirements, the average amount increases on an additional 3,000 euros (3,500 euros) for those who live in (away) their parents' home. Before 2013, there was an additional level of grant, the Displacement and Other Needs Grant (Threshold 3). This level of allowance provided students with different cash endowments as displacement to the university, urban transport, academic material or final undergraduate degree project. A student who received this grant (DG grant hereafter) could obtain only one or a combination of those different endowments.

Eligibility Rules. Students are eligible to the BCG grant if they are citizens of member states of the European Union, are enrolled in a Spanish higher education institution, and do not hold a degree of equivalent or higher level than the one they are applying for.[14] Students can receive a BCG grant for at most one year more than the official length of the program which they are enrolled in, and for a maximum of two additional years of the program length for students who are enrolled in STEM (Science, Technology, Engineering and Mathematics) degrees.

Grant eligibility is assessed on the basis of student needs and academic performance. The need condition is evaluated on the basis of the applicant's annual household income the year before application. Qualification for a grant and the amount awarded depend on the students' household taxable income, as well as the number of household members.[15] The applicant's annual household income is computed as the household taxable income minus specific quantities to which student's may qualify (such as large family or disability).[16] The grant can be denied

[14]From 2013 onward, students from post-compulsory degrees (such as college preparation or vocational track) in the educational system are also eligible. Detailed information about the students' eligibility rules is provided in *Real Decreto 1721/2007 de 21 de diciembre, Boletín Oficial del Estado (BOE)*. Furthermore, each courses application specifics are detailed 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.*

[15]The definition of a student's household includes the student's father, mother, siblings under the age of 25, 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 household members who live with the applicant are considered.

[16]For instance, if income sources are coming from any other household member but student's parents, the household is classified as large family, or there is a family disabled member, among others.

based on household income as well as when household wealth, family business activity and capital returns exceed certain thresholds.

Family income thresholds determine applicant's eligibility to different levels of grant depending on the number of household members. The fact that income eligibility thresholds change with the number of family members creates multiple discontinuities, which are graphically displayed in Figure 1. To be eligible to the first and second levels of grant (fee waiver and RG grant), for a household with four members (which is the average value in the sample), the annual family income must fall behind 38,831 and 36,421 euros respectively, which corresponds approximately to the fourth and top quintiles of the Spanish income distribution.[17] To be eligible to the highest level of grant (CG grant), the same household must earn less than 13,909 euros, which roughly corresponds to the bottom quintile of the income distribution in Spain.

The grant's academic requirement is met conditional on having passed a minimum fraction of credits the year before application. Applicants must be enrolled in at least 60 ECTS credits, which corresponds to the number of credits obtained in a typical academic year.[18] In 2013, the framework of the program and the performance-based incentives were modified.[19] From now on I will refer to the three academic year terms of 2010–2012 as Period I, and the years 2013–2015 as Period II, concerning two different BCG setups.

Freshmen students must show an average grade in PAU of: (i) 5/10 points (corresponding to having passed the university entrance exam) to qualify for all grant levels in Period I; (ii) 6.5/10 to qualify for all grant levels, and 5.5/10 to be only eligible for the fee waiver allowance in Period II. Students who are not in their first year of higher education, must provide evidence on have passed a certain fraction of credits the year before applying:

- *Period I (2010–2012)*: 60 percent if the student is enrolled on a STEM degree, and 80 percent in any other degree.
- *Period II (2013–2015)*: 65 (90) percent if enrolled on a STEM (non STEM) degree to be only eligible for the fee waiver endowment. In order to qualify for all grant types, the student must have passed either: (i) 85 (100) percent if enrolled on a STEM (non STEM) degree; or (ii) 65 (90) percent if enrolled on a STEM (non STEM) degree, plus

[17]Computations based on de España et al. (2017).

[18]There are some special exceptions where students are allowed to be enrolled in less than 60 credits, e.g. when the attended program is made of less than 60 credits per year or when the student is affected by a disability.

[19]Detailed information about the change in BCG setup is provided at the end of this section and in the online appendix, section F.

have obtained an average GPA of 6/10 (6.5/10) respectively for STEM (non STEM) degree.

Application Process. The allowance is set up on a yearly application process that is common to 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 submitted to the Ministry of Education. The application form consists of an online questionnaire. No document transfer is needed since the Ministry contacts directly the institutions concerned, i.e., the Tax Authority and the university where the student is enrolled.
- *December*: applications start to be denied for non-eligible students. Application outcomes are not necessarily disclosed at the same time for all applicants. Denied grants are revealed in December, on average, while awarded grants are notified after January until the end of the academic year.[20] Usually, the total amount granted is transferred to the students one month after the notification.

The unique application process of this program allows to estimate the cash allowance effect on student performance with no concerns of enrollment effects that may bias the results. Students are already enrolled at the higher education institution when they apply, and the vast majority of grant decisions are not notified before the end of the first term of the academic year. Hence, estimations are based on "intramarginal" students (students who would have enrolled in university irrespective of receiving financial support) and measure intensive margin responses.

The potential manipulation of information by applicants might be a concern for this type of allowances. It should be noted, however, that the Ministry directly contacts the Tax Agency and the university in order to check applicants' household income and academic status. Hence, students have only limited ability to misreport this information. A more serious concern is that students may be more likely to apply if they are below the income family thresholds, generating a discontinuity in application rates at the cutoffs. Before 2009, income eligibility thresholds changed every year complicating the applicant's knowledge of their accurate situation, but over 2010–2015, income thresholds remained unchanged. Discontinuities in application rates would be more likely to occur at the Fee Waiver grant cutoff, since, at other levels of grants, students

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

remain eligible for at least some form of aid (e.g., tuition fees) and hence have strong incentives to apply even if they anticipate being below the corresponding cutoffs. Moreover, the existence of multiple income reductions that affect the computation of students' annual household income, makes it difficult for students to accurately evaluate their relative distance to the grant eligibility cutoffs. The complexity of the eligibility rules may encourage students to apply even in cases when they are unsure on whether they meet the criteria. Manipulation on eligibility threshold is discussed extensively in section 5.1.

Change into the BCG grant: Period I vs. Period II. As mentioned previously, the grant structure was changed in the academic year 2013, affecting the design of the program and its performance-based incentive components.

First, in addition to the three main cash allowances, the previous framework included the DG grant, which was based on a number of criteria such as distance to university, educational material, academic performance, etc. In 2013, these different components were merged into a single individual variable element, with conceded allowance if the student's family income was below the RG threshold. The variable component of the grant is set at a minimum amount of 60 euros, and is computed as a deterministic function of the student's average GPA, the average GPA distribution of grant holders, the applicant's income, and the income distribution of all applicants.[21] Likewise, the average per capita cash allowance amounts were reduced from one period to the other, for those receiving the CG grant, and for those living away from their family and eligible to the RG grant (discontinuities in average grant amounts are discussed extensively in section 5).

Second, more demanding academic performance requirements were set to be eligible to the grant, as explained above in this section. Overall, performance-based requirements became more stringent. The changes between the two periods can be therefore summarized as: (i) an increase in the minimum fraction of credits passed the year before application; (ii) the inclusion of the average GPA the year before application among the academic performance requirements; (iii) the incorporation of the grant's variable component which award students with different grant amounts depending on their GPAs in the current academic year.[22]

[21] The exact formula of the variable component of the grant is provided in the online appendix (section F). The Ministry of Education offers an online simulator for the variables amounts at the following address: *http://www.mecd.gob.es/educacion-mecd/mc/becas/2016/estudios-universitarios/simulador.html*

[22] A detailed summary of the policy change regarding academic performance requirements is provided in the online appendix (section F).

3 Data and Descriptive Statistics

Data. The data used in this paper are 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. I exploit the *SIGMA* database which consists of four administrative data files, which can be matched on the basis of an encrypted student identifier: i) household information, ii) awarded grants, iii) university enrollment, iv) grades in university. The household information database contain the set of variables that determine grant eligibility (household taxable income, number of family members, household wealth, family business, large family condition and whether a family member suffers a disability), the administrative status of the scholarship (grant final status, denied reason and type of scholarship), and reference parent's occupation. The awarded grants database provide details about the BCG grant amounts, the type of allowance and the date of concession. The university enrollment database embrace information about grant applicants at the time they enter university, such as gender, nationality, postal code and the score in the *PAU* entrance exam. The database on university grades covers all academic curricula of students who at least applied once to the BCG grant between 2004 and 2015, providing information on the department, degree and subjects in which each student is enrolled, as well as each subject's course and the final grade obtained.

Sample restrictions. On average, 5,300 Carlos III students apply for a grant in a given year. Table 1 displays the number of BCG applicants by year and degree program. The analysis is restricted to undergraduate students, who represent 93 percent of total applicants. Graduate students are not included in the analysis due to their limited sample size, which separate estimations at each income-eligibility threshold would be imprecise. Moreover, I focus on students who were not denied the grant due to problems with the Tax Agency and were not declared ineligible by excess wealth or business income, in order to make the regression discontinuity design sharper.[23].

Descriptive Statistics. Table 2 shows descriptive statistics on the sample of BCG grant applicants who were considered in the analysis. I split the estimation sample into two groups: (i)

[23]Students excluded from the sample of analysis represented 16.17 percent of the total applicants over the six-year period. Excluding such students would be a problem if the probability of being denied a grant due to the reasons explained above was discontinuous at the grant eligibility cutoffs, thus leading to sample selection. This potential threat to identification is not a concern here, since rejection probabilities are continuous on either sides of the cutoffs (results available upon request).

the RG grant sample (Threshold 1) includes applicants who are in the vicinity of the RG grant threshold; (ii) the CG grant sample (Threshold 2) includes applicants whose relative household income is close to the CG grant threshold. Most of the applicants are Spanish, were living with their parents when they entered university, and are enrolled in non-STEM degrees. The average household taxable income is approximately 32,000 euros for the RG grant sample, and approximately 14,000 euros for the CG grant sample. The average household size is four people and 11 to 17 percent of applicants in the treatment samples qualify for the large family bonus. The majority of applicants' family head member worked as blue collar.

4 Conceptual Framework and Empirical Strategy

Conceptual Framework. A basic "law of behavior" is that stronger incentives should lead to more effort and higher performance (Gneezy, Meier and Rey-Biel, 2011). A number of studies have provided empirical support for the claim that the higher the payment, the higher the effort (Gneezy and Rustichini, 2000), but whether monetary incentives are large enough depends on the specific case under consideration. If incentives are sizable enough, their direct price effects will be larger than the crowd-out effect, but if they are too high, individuals can "choke under pressure" and incentives can backfire (Ariely et al., 2009).

A theoretical framework is convenient to rationalize the potential effects that grants may have on student performance under different cash amounts granted and performance standards, given individual income levels. Let student performance (y) depends on the cash amount awarded (a), the performance standards required (s), and the individual income level (c):

$$y = f(a, s, c) \tag{1}$$

where $f(.)$ is a deterministic function.

To simplify, assume that performance standards can be either high ($\bar{s}$) or low ($\underline{s}$), and that grant amounts may take three values ($a'' > a' > 0$). Generally, it is reasonable to expect positive performance differential effects for a marginal increase in the level of amount and performance standards, conditional on the level of income. Formally, $f_a(a, s, c) > 0$ and $f_s(a, s, c) > 0$.

Without loss of generality, define $\Delta y = f(a_1, s_1, c) - f(a_0, s_0, c)$, as the change in student performance under different levels of grant amounts (a_0, a_1) and performance standards (s_0, s_1).

This equation can be written as a function of the partial derivatives using a Taylor expansion:

$$\Delta y = f(a'', s, c) - f(a', s, c) \sim f_a(a', s, c) * (a'' - a') \tag{2}$$

where a' denotes the amount of financial aid above a certain cutoff and a'' the grant amount below the specific threshold. Intuitively, this can be interpreted as the performance differential effect of receiving a'' level of financial aid, relative to obtaining a' (where $a'' > a'$).

The two scenarios analyzed in this paper are the following:

(i) *Scenario 1: RG grant (cash grant amounts relative to zero).* Consider two different settings similar to the situations of Period I and Period II at RG grant threshold. A first setting where performance standards are weak ($\underline{s}$) and Δy_I^{RG} is defined as $f_a(0, \underline{s}, c) * a'$, and a second situation where performance standards are strong ($\bar{s}$) and Δy_{II}^{RG} is settle as $f_a(0, \bar{s}, c) * a'$, where the reference group is awarded with zero cash grant amount. Comparing both states lead to the following equation:

$$\Delta y_{II}^{RG} - \Delta y_I^{RG} = [f_a(0, \bar{s}, c) - f_a(0, \underline{s}, c)] * a' \tag{3}$$

Since a' is similar in both periods, the sign of this difference depends on the cross-derivative sign, $f_{as}(0, \underline{s}, c)$. The cross-derivative would be positive if a given increase in grant amount has stronger effects on performance when performance incentives are higher ($\bar{s}$ vs. $\underline{s}$). This scenario is comparable to the design of BCG at RG grant in the different periods. The average amount conceded is almost the same in Period I and Period II, but the incentive components are more demanding in Period II than in Period I.

(ii) *Scenario 2: CG grant (cash grant amounts relative to a').* Consider two different scenarios similar to the situations in Period I and Period II at CG grant threshold. A first setting where performance standards are weak ($\underline{s}$) and Δy_I^{CG} is defined as $f_a(a', \underline{s}, c) * (a'' - a')$, and a second situation where performance standards are strong ($\bar{s}$) and Δy_{II}^{CG} is settle as $f_a(a', \bar{s}, c) * (a'' - a')$, where the reference group is awarded with certain cash grant amount a'. Comparing both states lead to the following equation:

$$\Delta y_{II}^{CG} - \Delta y_I^{CG} = \left[f_a(a', \bar{s}, c) - f_a(a', \underline{s}, c)\right] * (a'' - a') \tag{4}$$

In this situation, the result is non-trivial. First, since $(a'' - a')$ is larger than a' (the cash grant amount awarded in CG grant is larger than in RG grant), and the sign of the difference depends on the cross-derivative $f_{as}(a', \underline{s}, c)$ evaluated at a higher level of grant than in scenario 1, it may be the case that higher increments of grant amounts lead to higher performance enhance in a setting with more demanding performance standards. On the other hand, as $a' > 0$, following Kahneman and Tversky (1979) and Tversky and Kahneman (1991) notion of reference dependent preferences and *loss aversion*, along with papers testing this type of behavior in the education literature (Fryer et al., 2012; Levitt et al., 2016), it may be the case that the cross-derivative, evaluated at greater amount of grant, is close to zero, regardless of the performance standards required. This concept shows that people underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty, and this tendency contributes to risk aversion in choices involving sure gains and to risk seeking in choices implicating sure losses. In scenario 1, students are awarded with financial aid relative to zero cash amount. In scenario 2, students are grant awarded relative to a positive reference cash amount (a'). The opportunity cost of not complain with the grant performance standards for the reference group (i.e., those students who are not receiving the grant) is lower in scenario 1 (zero) than in scenario 2 (a'). As the reference group is awarded with certain cash amount in scenario 2, it is likely that they behave as loss averse and the potential loss encourage them to perform better. This scenario is comparable to the design of BCG on CG grant in the different periods. The average amount conceded and the grant quantity starting with are larger than in RG grant, but the incentive components are more demanding in Period II than in Period I.

Therefore, it seems clear that $f_{as}(a, s, c) > 0$ when evaluated at a equal to zero (i.e., an increase in grant amount will have larger effect on performance when incentives are stronger), but it may be that when evaluated at high enough a, $f_{as}(a, s, c) \sim 0$ (i.e., the effect of an increase in grant amount on performance, starting from large a, will not be higher when performance incentives are stronger), or $f_{as}(a, s, c) > 0$ (i.e., an increase in grant amount will have larger effect on performance when incentives are stronger, irrespective of the amount of financial aid starting with).

Empirical Strategy. The goal is to estimate the causal effect of being eligible for a need-based grant on student performance and degree completion under two different grant settings. The estimates of a simple OLS regression of college achievement on a dummy variable indicating whether the student receives a grant would be subject to omitted variable bias, even after controlling for observable characteristics such as parental income, gender or predetermined ability measures, since the investigation would not account for unobservable determinants of student performance that are likely to be correlated with financial aid status (e.g., motivation).

To identify the treatment effect of being eligible for a need-based grant, I exploit the sharp discontinuities in the amount of cash allowances awarded using a regression discontinuity design (RDD). The BCG grant generates two different discontinuities at the RG and CG grant eligibility thresholds. Let $E_{i,k,t}$ denote 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}:

$$E_{i,k,t} = \mathbb{1}\{c_{it} \leq \bar{c_k}(m_{it})\} \tag{5}$$

where $\mathbb{1}\{\cdot\}$ is the indicator function and $\bar{c_k}(\cdot)$ is a deterministic function that returns the household taxable income threshold when the number of family members is m_{it}.

Let A_{it} denote the amount of conditional aid awarded to student i at time t. The total amount granted is determined as the sum of the different allowances increments $\alpha_{k,p}$ for which students are eligible at k level of grant in period p, where $p = 1$ for Period I (2010–2012) and $p = 2$ for Period II (2013-2015):

$$A_{it} = \mathbb{1}\{t \leq 2012\} * \sum_{k=1}^{2} \alpha_{k,1} E_{i,k,t} + \mathbb{1}\{t > 2012\} * \sum_{k=1}^{2} \alpha_{k,2} E_{i,k,t} \tag{6}$$

The allowance increments in Period I and Period II are defined as follows:

$$\alpha_{k,1} = \gamma_{k,1} \tag{7}$$

$$\alpha_{k,2} = \gamma_{k,2} + \mathbb{1}\{t > 2012\} * z_i(c_i, \overline{c_i}, g_i, \overline{g_i}) \tag{8}$$

where $\gamma_{k,1}$ and $\gamma_{k,2}$ are period-specific fixed amounts, and $z_i(\cdot, \cdot, \cdot, \cdot)$ is a deterministic function that returns the amount of variable component granted to applicant i with household income c_i and grades g_i when average household income and average grades among applicants are $\overline{c}_i$ and $\overline{g}_i$ respectively.

The reduced-form equation capturing the relationship between the eligibility formula and the outcome variable is the following:

$$Y_{it} = \alpha + \mathbb{1}\{t \leq 2012\} * \sum_{k=1}^{2} \beta_{k,1} E_{i,k,t} + \mathbb{1}\{t > 2012\} * \sum_{k=1}^{2} \beta_{k,2} E_{i,k,t} + \epsilon_{it} \tag{9}$$

where Y_{it} is the outcome variable of student i at time t and ϵ_{it} are residuals of individual i at time t. In equation (9), the parameters $\beta_{k,p}$ are the treatment effects of being eligible for a grant k at period p.

Several identification assumptions are needed in order to identify a causal effect. I assume that the conditional distribution function is smooth in the forcing variable, and that there is no observed jump in the conditional probability of the outcome variable at every point of household income. In the absence of treatment, the outcome variable is a smooth function of parental income. Under this assumption, the causal effect of being eligible for a BCG grant of level k is identified by comparing outcomes for applicants who are close but below the eligibility income threshold (treatment group) with students who are near but above (control group). Thus, the local average treatment effect of being eligible for a BCG grant of level k relatively to a grant of level $k-1$, in period p, is identified as:

$$\beta_{k,p} = \lim_{c \uparrow \bar{c_k}(m)} E[Y \mid c, m, p] - \lim_{c \downarrow \bar{c_k}(m)} E[Y \mid c, m, p] \tag{10}$$

A specific feature of the BCG design is the existence of multiple income eligibility thresholds. In total, there are 22 distinct eligibility cutoffs for the RG and CG grants, depending on the applicant's household size (see Figure 1). To have sufficient statistical power, I pool all thresholds that are associated to a given level of grant,[24]. The two treatment samples are defined as follows: (i) the first sample combines the eleven household taxable income cutoffs of the RG grant. In this sample, I identify the $\beta_{1,1}$ and $\beta_{1,2}$ treatment effects of being eligible for an approximate average cash allowance of 567 euros and 760 euros respectively, relatively to being eligible for fee waiver only. (ii) the second sample combines the eleven parental income thresholds of CG grant. In the second treatment sample, I identify the $\beta_{2,1}$ and $\beta_{2,2}$ treatment effects of being eligible for an approximate additional average cash allowance of 2,798 euros and 1,219 euros respectively,

[24] Note that the fee waiver eligibility threshold is close to the eligibility cutoff the the RG grant (as observed in Figure 1) making difficult to construct two treatment samples (with sufficient number of observations) between RG grant and fee waiver which do not overlap. The discontinuity induced by the tuition fee eligibility cutoff is therefore ignored in the main analysis. However, as a robustness check, I conduct a separate analysis of the treatment effect of tuition fee eligibility. The results (reported in the online appendix, section D) show no evidence of statistically significant effects on student outcomes at this income-eligibility threshold.

relative to being eligible for RG grant (567 euros and 760 euros respectively).

Notice that the framework offers a clear advantage to identify the effect of incentive components alone, since the difference between $\beta_{1,1}$ and $\beta_{1,2}$ are the more demanding performance standards of the second period, under very similar average cash allowances on both periods (less than 200 euros of difference). In contrast, $\beta_{2,1}$ and $\beta_{2,2}$ identify the effect of the program under different performance standards and average cash allowances granted (1,579 euros), blurring a clear distinction between incentives and income effects.

Following Lee and Lemieux (2010), the treatment effects are estimated using a rectangular kernel.[25] The standard errors are computed using standard least squares methods (robust standard errors) clustered at the student level.[26] The bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2012).

A reasonable potential concern regards the presence of treated (untreated) students for complaining (not meeting) the academic requirements in both sides of the income-eligibility thresholds. A potential empirical analysis to account for it may be to develop a two-dimensional RDD, with two running variables: relative distance to income-eligibility thresholds, and distance to the academic requirement thresholds. Two problems arise to implement this type of RDD. First, due to sample size limitations, separate estimations at each academic requirements threshold would be very imprecise. Second, there are multiple academic requirement thresholds, since in the second period additional thresholds where incorporated in order to combine the fraction of credits passed and average GPA on the year before application. The presence of multiple dimensions of academic cutoffs reduces the sample size even more and complicate the identification (a normalization for all academic cutoffs may be a solution but results would be difficult to interpret). Likewise, the proportion of students who were denied a need-based grant for not complained with the performance minimum standards was 6.6 and 8.6 percent in the RG and CG grant treatment samples respectively. In the online appendix (section D), I perform a robustness check testing the significance of the baseline results on a treatment sample that do not include students who did not complain with academic standards. The results are robust to this test.

[25] Results are larger and robust when a triangular kernel is used. Results available upon request.

[26] Standard errors are clustered at the student level due to the fact that the same student may be observed several times in the same treatment sample if she applied more than once in the period studied.

5 Results

5.1 Internal Validity of the Empirical Strategy

The internal validity of the RDD requires that there is no endogenous sorting on either side of grant eligibility cutoffs. This behavior may lead to a continuity break in applicants' density at the cutoff, and would imply that the treatment group (eligible students) cannot be compared to the control group (non-eligible students). As emphasized by Imbens and Lemieux (2008), this type of endogenous sorting is more likely to occur in the common case where the treatment assignment rule is public knowledge, as in this setting. Since precise thresholds are public information and have not changed since 2010, a concern of manipulation at the cutoff arises specially for the first income-eligibility threshold (fee waiver). In contrast, manipulation is less likely at higher cutoffs, since students have incentives to apply on either side given the fact that students on both sides are awarded with certain amount of aid.

A formal investigation of the non-random sorting of applicants at the income eligibility thresholds is key to the validity of the RDD estimation strategy. McCrary (2008) proposes a test based on an estimator for the discontinuity in the density function of the running variable at the cutoff, checking the no systematic manipulation of household parental income around the thresholds. Figure 3 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 grant. As expected, density of applicants increased as parental income decreased in RG grant, given the fact that more students may be encouraged to apply as they were closer to the cutoff. Density estimates at CG grant were roughly constant, since applicants have incentives to apply on both sides as they would be awarded with fee waiver plus a positive cash allowance. McCrary test statistics confirm that the null hypothesis of no density jump at the eligibility cutoffs cannot be rejected.[27]

An additional test for local random assignment is to check whether applicants baseline characteristics are "locally" balanced on either side of the thresholds. If some groups of students are more likely to sort on the "good" side of a threshold may indicate endogenous sample selection, and treatment assignment cannot influence variables that are predetermined with respect to the treatment. Local linear regressions are performed for each of the applicants' observable characteristics (gender, nationality, parental income, PAU score and parents' occupation, among others)

[27] See online appendix (section B) for details of McCrary test's estimates for all treatment samples used in this paper (i.e., by period, gender, predetermined ability, etc.).

as dependent variable. Panel A of Table 3 presents the regression results, showing that none of the baseline students' characteristics change discontinuously at income eligibility thresholds, since none of the coefficients are statistically significant. Furthermore, I 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. A chi-squared test based on a system of seemingly unrelated regression with as many equations as baseline characteristics is performed. Panel B indicates that the null hypothesis that the discontinuity gaps are jointly equal to zero cannot be rejected.

An additional concern is that parental income, at constant prices of 2015, was highly correlated over time (regressing applicants' income in a given year on income the year before leads to a coefficient estimate of 0.73), which may lead to a persistent sorting of applicants on either side of eligibility cutoffs and may confound the effects of current year discontinuities in grant amounts with those from previous years. In fact, there was variation in income, since the fraction of applicants who reported the same parental income than the one registered the year before was only 3.2 percent, which may explain why there was no endogenous sorting in the previous tests. Students' who were awarded a grant in a given year might be more likely to re–apply the next year, especially for those below the cutoff of the RG grant. It may suggest that impacts would be driven by this group, with no density break for applicants at the cutoffs but so for re–applicants. A robustness check testing the discontinuity in the density of re-applicants cannot reject the null hypothesis of zero discontinuity in re-applicants' density.[28]

5.2 Discontinuities in Grant Amounts

In this subsection, I examine the discontinuities in average grant amounts awarded on the income-eligibility thresholds, which is a necessary condition for the empirical design to identify the causal effects of grants on student outcomes.

Figure 4 shows the average fraction of applicants who were awarded either with a RG or CG grant plotted against the relative income-distance to the relevant eligibility thresholds. The figure indicates that 90 percent of the applicants received the grant. The remaining 10 percent are applicants who either did not comply with the grant achievement criteria or the Tax Agency found administrative problems with their tax records.

Figure 5 presents the average conditional grant amount for all treatment samples as a function

[28]See online appendix, section B.

of applicants' relative distance to the thresholds over the two periods under study. The results indicate a clear discontinuity in the average conditional cash allowance for RG and CG grants over the two periods, reinforced by the statistically significant results showed in Table 5 (Panel A). RG grant provides a similar average grant amount for both periods, with an average cash amount of 567 euros in Period I and 760 euros in Period II (relatively to been awarded with fee waiver). CG grant reports a drastic decrease in the average grant amounts awarded between periods, with an average increment in the cash amount of 2,798 euros in Period I and 1,219 euros in Period II (relatively to RG grant cash awards).

5.3 Impact on Student Performance

I focus on the average GPA as a measure of student performance, which in Spain can take values between 0 (the minimum grade) and 10 (the maximum).[29] Likewise, results are robust to using other measures of student performance, such as the fraction of credits passed over the total credit attempted (Panel C of Table 5).

Baseline Estimates: current year effects. Figure **??** plots the average GPA for all treatment samples as a function of applicants relative income-distance to the thresholds over the two periods studied. The solid black lines are the fitted values from a quadratic polynomial approximation. The average GPA is similar across the two samples of applicants (around the RG and CG grant thresholds respectively), but over time, the average GPA was around 5.9 points in Period I and 6.15 points in Period II. Table 5 presents the RDD estimates (Panel B). I find no effect of relatively large cash allowance (neither for 567 nor for 2,798 euros) on student performance in Period I, when performance requirements were comparable to the weak performance incentives that characterize the typical need-based grant programs around the world. By contrast, I find that being eligible for an average grant of 760 euros (relatively to being eligible for fee waiver) in Period II, when performance requirements were made more stringent, increased students' average GPA by 0.46 points, which corresponds to an increase of approximately 7.6 percent with respect to the baseline mean. Furthermore, being eligible for an average grant of 760 euros (relatively to being eligible for fee waiver) in Period II, increased the students' fraction of credits passed of approximately 6 percent with respect to the baseline mean.[30]

[29]GPA's 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+.

[30]In online appendix, section E, displays a t–test of the difference in baseline means of students' observable characteristics by period and treatment sample, for an attempt to test the comparability of the two periods for

The RG grant threshold offers a unique opportunity to analyze the role that performance-incentives play in BCG grant, since average grant amounts were very similar between Period I and Period II (527 vs. 760 euros), but performance-based incentives were different. The results suggests that academic incentives augment the effectiveness of aid in improving student performance. The interpretation of the non-significant results at the CG threshold over the two periods is ambiguous. It can be explained through a loss aversion behavior, i.e. the incentive components affect differently students who are entitled to different levels of grants (the loss opportunity cost of not complain with academic standards is higher at CG grant than at RG grant), though the incapacity of the poorest students (CG grant applicants) to react to incentives due to their lack of ability for developing effective study strategies, or as the positive effect of a higher incentive component being offset by the negative effect of large decrease in the cash allowance awarded between Period I and Period II.[31]

Baseline estimates are robust to several specification checks. The sensitivity of the baseline results is tested by investigating different bandwidth selection criteria, where the bandwidth is set to be half and twice as large of the optimal bandwidth proposed by Imbens and Kalyanaraman (2012), and by performing the local polynomial regression with robust bias-corrected confidence intervals proposed by Calonico, Cattaneo and Titiunik (2014). Moreover, the baseline results are robust to control for applicants' predetermined observable characteristics as well as year fixed effects that capture time trends in the outcome variable. The results are robust to all different specifications and vary from an effect of 0.27 to 0.5 points, which corresponds to about 4.5 to 8.3 percent with respect to the baseline mean.[32] Although the magnitude of estimates varies across specifications due to the limited sample size, the direction of the effects hold over the different specifications, indicating a robust impact of grant eligibility on student performance when the academic standards were stronger. In addition, the null effect of the grant under the other different thresholds (CG and fee waiver grant) and periods is also robust.[33]

Most of the literature focuses on the extensive-margin effect of grants on enrollment, mainly for entry students. When there is an effect on enrollment (which is often stronger for freshmen students), disentangle the intensive margin response on performance is challenging (due to the

each of the two allowances studied. The null hypothesis of equality of the observable characteristics between periods cannot be rejected for three quarters and more than half of the variables in RG and CG respectively.

[31] The interpretation of the results is discussed extensively in the Discussion section of the paper.

[32] The results of each robustness check are presented in the online appendix, section D.

[33] The null effect of the grant at the Fee Waiver cutoff, where students are relieved from tuition fees but are not granted with cash amounts are presented in the online appendix, section D.

potential bias that the enrollment effect provides). An advantage of this paper's identification strategy is the specific timing of grant applications in Spain, that allow to estimate their effects on students who are already enrolled, and for whom dropout rates are relatively small. Table 6 displays the RDD estimates on university dropout. The null hypothesis of a zero effect of cash allowance on dropout cannot be rejected for all types of grants and periods. The results are reassuring the fact that the effect of the grant on student performance is not biased by the dropout effects.

Persistence of effects over time. Being eligible for a need-based grant may have dynamic effects over students' academic careers. Grants may produce long-lasting effects over time impacting students outcomes in several subsequent years. I compute the effect of being eligible for a grant on applicants' cumulative performance over several academic years: conditional on applying for a grant at time t with a certain household income, it is possible to compute the cumulative average GPA over subsequent years. This method would provide unbiased estimates and no sample selection concerns, but potentially the first stage would decrease over time due to the variability of applicants' application status and household income over years.[34] Local linear regression estimates indicate that being eligible for a grant under strong performance-based incentives increased the cumulative average GPA over two years by 0.39 points per year, which corresponds to an increment of about 6.5 percent per year 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 (2012),with results ranging from 0.23 to 0.39, which corresponds to a 4.0 to 6.5 percent increase 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 local polynomial regression with robust bias-corrected confidence intervals proposed by Calonico, Cattaneo and Titiunik (2014).[35] Need-based grant with high performance standards seems to have a positive impact on student performance that last for two consecutive years.

[34]First stages and a test for discontinuity in the density function of the running variable at the cutoff are presented in the online appendix, section C.

[35]Results available upon request.

5.4 Heterogeneous Effects of the Impact on Student Performance

Despite of the robust baseline estimates, investigating the existence of heterogeneous results for different subgroups of population is necessary to understand if there are differential effects by gender, predetermined academic ability and residence status, using separate regressions for each of the subgroups.

Table 8 presents the RDD estimates for the RG and CG by period and sample subgroups. The positive effects of the RG grants on student performance coupled with more stringent performance incentives are found for both males and females, but the magnitudes differ (Panel A). The coefficient estimates are statistically significant and indicates that being eligible for a RG allowance under strong academic incentives has larger effect on performance for males than for females, with the difference across gender being statistically significant. Panel B explores heterogeneous effects by academic ability. Being eligible for a RG grant in a setting with high incentives has significantly positive effects on student performance for students both above and below the median percentile rank in *PAU*. The null hypothesis that both effects are equal across groups below and above the median cannot be rejected. Panel C presents the results divided by the different applicants' residence conditions. It seems that the positive impacts are driven by applicants who were living with their parents in the Region of Madrid (non-movers hereafter) when they enter university, while students who were living away from their family home (movers hereafter) are not affected by grant qualification. The null hypothesis of equality of coefficients is rejected. While students living away from their 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.[36] The grant structure allows 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 components were weaker. A change from zero to a positive cash allowance of 410 euros, interacted with strong academic incentive components leads to a positive impact on students' average GPA of 0.41 points (7 percent with respect to the baseline mean).

The importance of the performance standards intensity. Figure 5 and Figure **??** display the fact that with similar average cash amount granted, an allowance setting with strong performance-based components is more effective at enhancing student performance, as opposed

[36]See online appendix, section C.

to a setting with weaker incentives. Nevertheless, Table 8 shows that the effect is only driven by non-movers. Those students received zero cash allowance in Period I, but 410 euros on average in Period II, while the effect is only statistically significant in Period II. Effects might be derived by the cash allowance award, the performance-based incentives or the complementary of both. In order to test the policy's efficiency, a deeper inquiry is needed.

An ideal test would be a similar amount of cash awarded for non-movers at Period I and II for RG grant, but unfortunately this is not the case. As a robustness check, I use the DG grant for non–movers as comparison group for RG non–movers at Period I, since both thresholds are very close to each other.

This analysis is useful to investigate the role of grant's performance-based incentive components. The key advantages of using the DG cutoff are twofold. First, the DG grant was located 15 percent of the relative distance below the RG threshold, which mitigates concerns regarding the comparability of students in the vicinity of these two cutoffs. The sample of non-movers received their first cash award at DG in Period I, which makes the comparable group similar to non-movers at RG in Period II. Second, the discontinuities in average cash grant amounts were very similar (543 vs. 410 euros). Hence, using non-movers in Period I for DG grant as a comparison group for RG non-movers in Period II is convenient due to the fact that it offers an scenario where entitlement to the grant, cash allowances and sample are comparable, but performance-incentives are different in the two periods.

The average increase in cash allowance at DG in Period I was 543 euros for non-movers, and cash endowments at RG in Period II was 410 euros for non–movers. However, the null hypothesis of zero effect of being eligible for the DG grant on non-movers student performance cannot be rejected. Results are robust to different treatment sample sizes, regarding the predetermined characteristics of applicants, year fixed effects, to set the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) 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).[37]

Student performance was not impacted by DG grant in Period I, and it was positively impacted in Period II by the RG, under approximately the same cash allowance amounts but different incentives. This finding suggests that performance-based incentive components seems

[37] See online appendix (sections B, C and D) to see the validity of the research design, the discontinuities in grant amount and the RDD estimates.

to play a crucial role on enhancing student achievement. Nevertheless, performance standards alone do not seem to be enough to improve student outcomes, since monetary incentives appear to be also crucial (there is no grant effect on fee waiver grant). The results point out to a complementarity between certain cash allowance and strong performance-based incentives as drivers of the grant's effect on performance.

5.5 Mechanisms

The goal of this section is to analyze whether the performance increments observed are due to an actual rise in student success or are spurious, e.g. if they are driven by students taking easier subjects. Table 9 presents the results of the RDD estimates on different variables for RG and CG by period, and Figure 9 plots these different channels, reinforcing the results of the non-parametric estimates.

Final exam attendance rate. Panel A shows that being eligible for an average cash allowance of 760 euros (relative to fee waiver only) increased the final exam attendance rate when performance incentives were more demanding. Although the average fraction of grant applicants who attended final exams was already high (92 percent), qualifying for such level of grant enhances this average by 3.3 percentage points, which corresponds to an increase of about 3.6 percent with respect to the baseline mean.

GPA on final exams taken. Students may attend with higher frequency to final exams, while their performance on them may remain unchanged. The fact that students showed-up more often to final exams may enhance their total average GPA due to the less frequent inclusion of subjects graded as zero points (grade given to students who fail to attend) in the total average GPA computation, but no for actual improvement in their performance. To test this hypothesis, I examine the discontinuity in the average GPA on final exams taken, in order to capture the increase in performance over the subjects that students finally took. Panel B displays that students who were eligible for an average cash allowance of 760 euros (relative to fee waiver only) under a setting with strong performance-based incentives improved their average GPA in final exams taken by 0.24 points, which corresponds to an increase of about 3.7 percent with respect to the baseline mean. The null hypothesis of zero effect is rejected at the 5 percent confidence level, indicating a genuine improvement in student performance.

Selection on courses. The need-based grant seems to help students to perform higher on subjects attended to the final exam. Even so, applicants may self-select on easier subjects when they are below the income eligibility thresholds, in order to increase their probability to meet the performance standards for grant renewal for the next academic year or enhance their probability to receive a higher amount of grant in the current year thought the variable component. Then, the average selection on courses may be different on both sides of the cutoffs, leading to a positive impact on performance which would be difficult to interpret. An intuitive measure of selection on courses would be to compute the average GPA by subject-year, and then compute the average subject-GPA over the total subjects that a student enroll by year. Though, this measure is strongly correlated with applicants' average GPA, especially in the same academic year, leading to endogeneity concerns. To test this conjecture, I examine the discontinuity of the average academic ability of the students' enrolled in each subject. First, I compute the average academic ability (measured as the percentile rank in PAU access to university test) by subject-year. Second, I calculate the average academic ability of the total subjects enrolled in by student-year. Since relatively better performing students tend take more challenging subjects, this measure provides a proxy for the degree of subject selection. Endogeneity concerns of this variable given by subject-grade-student selection are relaxed by choosing a predetermined measure of academic ability, which may be correlated with the average GPA but not endogenous to it. There is no evidence that being eligible for an average cash allowance of 760 euros (relative to fee waiver only) under strong academic standards impact the students' selection on courses. The null hypothesis of an allowance qualification effects on the average selection on courses cannot be rejected.

GPA on mandatory and elective subjects. Finally, I investigate the differential results on the average GPA for mandatory and elective courses as an additional test. Students are required to pass a certain number of elective courses chosen from a determined set of subjects which are degree-course specific, and several mandatory courses which are compulsory and degree-course specific. If applicants were to self-select in easier subjects, it is reasonable to expect it to happened for elective courses, due to the fact that such courses were those for which students had room for subject selection. Panel D and E analyze the effects of the grant on the average GPA for mandatory and elective courses. The results clarify that the effect is driven by an increase in the average GPA on mandatory subjects, since applicants who were eligible for an average cash allowance of 760 euros (relative to fee waiver only) under strong performance-based incentives, increased their average GPA by 0.43 points, which corresponds to an increase of 7 percent with respect to the baseline mean. Despite the higher average GPA on elective courses compared with mandatory, the null hypothesis of zero grant effect on average GPA in elective courses cannot be rejected.

5.6 Impact on Degree Completion

Table 10 expands the analysis by investigating the impact of financial aid on degree completion. The table focuses on students who applied for the grant in the final year of a degree program, i.e., in their fourth year of a bachelor's degree. The non–parametric estimates indicate that being eligible for 760 euros (relatively to the tuition waiver) in the period when performance requirements were more stringent, increased student's chances of obtain a degree by 8.3 percentage points, which corresponds to an increase of approximately 9 percent with respect to the baseline mean. In contrast, the null hypothesis of zero effect on degree completion under a setting with the typical performance incentives of the national large-scale need-based grant programs around the world cannot be rejected.

6 Discussion

The Spanish national need-based grant program provides a unique design to analyze its causal effect on student performance and graduation. I find no effect of relatively high cash amounts on student performance (average GPA and fraction of credits passed) and degree completion in a setting with weak performance incentives comparable to the typical need-based grant programs around the world. In contrast, I find that an average provision of 760 euros cash allowance (relatively to receive only fee waiver) increased student performance and probability of degree completion in a setting with more demanding performance-based incentives. Students also enhance their final exam attendance rate and their GPA on final exams taken. There is no concerns on student selection on courses or dropout effects that may bias the results.

6.1 External Validity

The estimates are based on a sample of low-income high school graduates enrolled in Carlos III University who applied to a BCG grant to start or to continue undergraduate college studies.

Carlos III University is a public higher education institution. An analysis comparing the educational attainment of Carlos III students with the rest of collegian enrolled in Spanish public universities presents that these students scored higher in the standardized university access exam, reported higher graduation rates and presented lower dropout rates (among other measures) than the rest of their fellows in Spain. However, the group of students who drive these differences are non-BCG grant recipients. In contrast, BCG grant recipients in Carlos III are highly comparable with BCG grant recipients in Spain, reporting similar GPAs, number of credits passed (over the total credits enrolled and the final exams taken), and time to graduation.[38] The sample of grant applicants is reasonably representative of the general population of low-income students in Spain. This group can be considered as comparable to the typical targeted population of most large-scale need-based grant programs around the world, e.g students graduated from high school and admitted to college. The results cannot be directly extrapolated to the population of low-income students who fail in high school graduation and might respond differently to financial aid, whereas they can be comparable to non-traditional students.[39]

The institutional features of higher education systems are decisive for the external validity of the results. Spain is part of the group of countries (along with France, Italy, Belgium or Austria) where post-secondary systems are mainly public and tuition fees charged are relatively low (OECD, 2016). In these countries, the student level of debt is considerably low, and the need-based programs cover tuition fees and part of the living expenses for low-income students. The results of this paper cannot be immediately compared with the US students who are not eligible to fee waivers (e.g. the Pell Grant), due to the fact that they present substantially larger levels of debt, higher tuition fees, and greater probabilities of working to pay for college. On the other hand, the effects of this paper are potentially comparable to the population of US students who are entitle to both fee waiver and need-based grants.

6.2 Interpretation of Results: Efficiency, Equity and Grant's Design

This paper points out to the importance of performance-incentive schemes on need-based grant's cost-effectiveness. From the efficiency point of view, a program with strong academic requirements presented a differential performance improvement for those students whose comparison group was receiving only fee waiver and zero cash amount. By contrast, the grant did not

[38] Details of the analysis are provided in the online appendix, section A.

[39] The Spanish BCG grant eligibility criteria do not impose any upper age limit, neither as the US Pell Grant.

seem to affect performance of those students whose comparison group was awarded with certain cash amount, neither under a setting with weak academic standards nor stronger performance-based components. Two hypothesis may help to interpret the results. First, the results seem to be consistent with the large literature on reference dependent preferences that demonstrates behavior consistent with a notion of *loss aversion* (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991), including papers testing this type of behavior in the education literature (Fryer et al., 2012; Levitt et al., 2016). This concept presents that people underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty, and this tendency contributes to risk aversion in choices involving sure gains and to risk seeking in choices implicating sure losses. An increase in the provision of financial aid on a group of low-income students whose counter-factual was receiving a certain positive cash amount does not appear to have a differential effect on student performance, due to the fact that the reference group may behave as loss averse, independently of the magnitude of performance incentives. The opportunity cost of not complain with performance standards is higher when some previous cash amount was awarded. This result is consistent with Fack and Grenet (2015), which largest effects of the French national need-based grant program were concentrated on those students receiving the first endowment of cash allowance and not for students entitled to higher levels of grant. In addition, several studies find large behavioral responses to small-scale interventions (Bettinger et al., 2012; Hoxby, Turner et al., 2013). Second, the null impact of the grant may be due to the fact that the poorest students are not as able as their peers to respond to performance incentives, even under the fairly large cash amounts granted. This result is consistent with Fryer (2011), which found no effect of financial incentives on student achievement on a sample of urban schools in the US. Perhaps, the muted effectiveness of the grant on those students may partly reflect the trouble struggling students have developing effective study strategies (Angrist, Oreopoulos and Williams, 2014; Daly and Lavy, 2009; Fryer, 2011).

It is not entirely clear that these hypothesis are the solely explanations. RG grant offers a unique setting to test the effects of performance standards alone by comparing both periods with broadly the same income effect but different incentives. In contrast, the same comparison is not possible for CG grant, since it is not viable to investigate whether low-income students would react under the same income effects on both periods but different incentives. The large decrease in average amounts between periods may offset the positive effect induced by the stronger performance standards presented at this grant level. In this setting the "law of behavior" which states that incentives are stronger when amounts are higher is only verified at the extensive margin of the entitlement to the grant.

From an equity stance, there is no evidence of an effect of the grant on dropout from higher education, neither for students whose comparison group was awarded with fee waiver nor for those whose counter-factual group was receiving certain cash amount. Stronger performance standards do not seem to induce grant applicants to significantly dropout with higher intensity. These results seem to contradict the evidence that performance incentives have negative impacts on student persistence (specially for those lower in the ability distribution) showed by Scott-Clayton and Schudde (2016). Perhaps the discouragement effects are concentrated on non-grant applicants, who could perceive the academic standards as draconian.

The results support a need-based grant setting with stronger academic requirements than the typical need-based grant programs around the world. A framework with such level of incentives seem to be the clear driver of the increase in student achievement and degree completion, and therefore, to enhance grant's efficiency at least for those low-income students whose comparison group was awarded with zero cash amount. Overall, the grant appear to be cost-effective under this structure, at least partially.

The design of performance-based incentives on need-based grants is an important policy question. Scott-Clayton and Schudde (2016) suggest that some minimum performance standard is desirable. Scott-Clayton (2011) shows that incentives tied to minimum course loads (not just GPAs) may be one promising tool for increasing educational attainment and speeding time-to-degree. The results of Angrist, Oreopoulos and Williams (2014) and Angrist, Lang and Oreopoulos (2009), along with the evidence showed in Cha and Patel (2010) and Barrow et al. (2014), among others, suggest that students react to thresholds targets more strongly than to marginal incentives beyond the initial target. Broadly, a performance standard framework with clear minimum thresholds targets combining minimum course loads and certain GPAs seems to be desirable.

6.3 Further Research

Further research needs to be undertaken to identify potential equity effects of such a grant design change, which requires assessing the potential adverse effects of performance-based incentives on college dropout for low-income students. Although the paper does not raise equity concerns among grant applicants, with the available data it is not possible to determine whether college entrants and continuing students were discouraged to enroll or to apply to the grant under such performance-incentive scheme. Despite the clear effect on student performance, further investigation on non-applicants' college dropout effects is required to fully conclude that the new setting is cost-effective.

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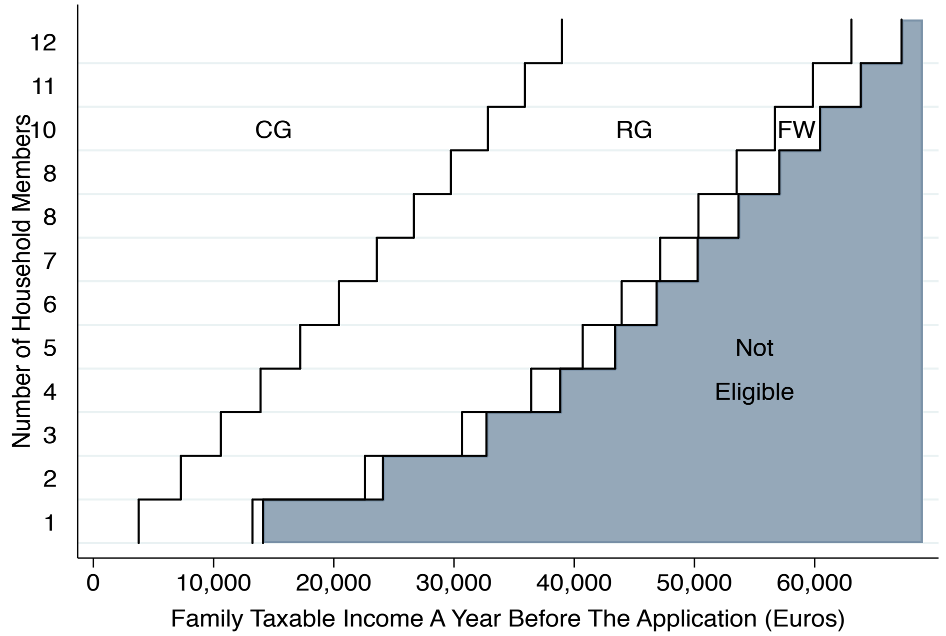
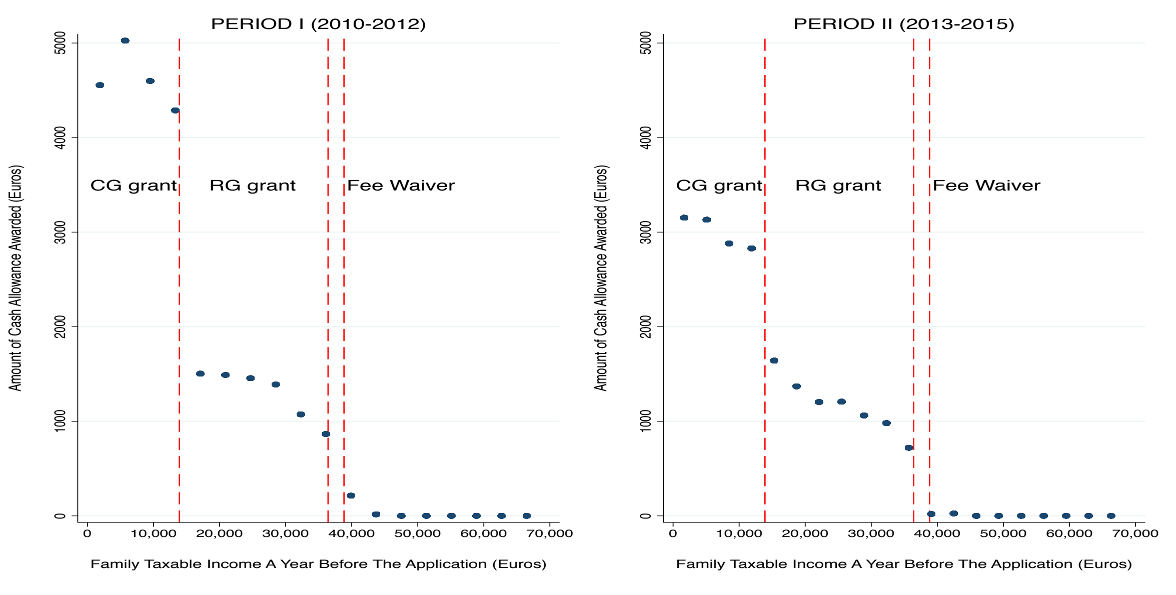
Figure 1: Income eligibility thresholds for the different levels of the BCG grant.



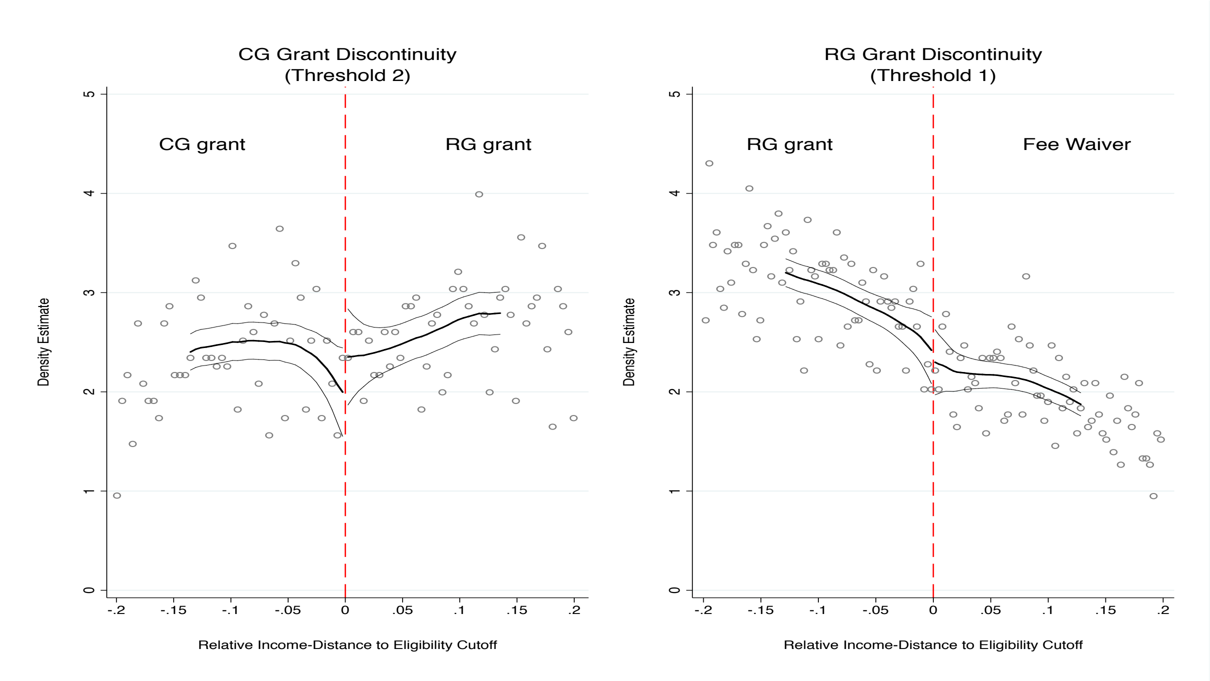
Notes: The figure depicts family income thresholds for different number of household members in the period 2010–2015. Thresholds are exactly the same amounts over the six-year period. FW refers to the fee waiver grant (Threshold 0), RG to Threshold 1 endowment, and CG to Threshold 2 allowance. Thresholds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

Figure 2: Amount of annual cash allowance awarded to applicants with 4 family members, as a function of their parents' taxable income by period



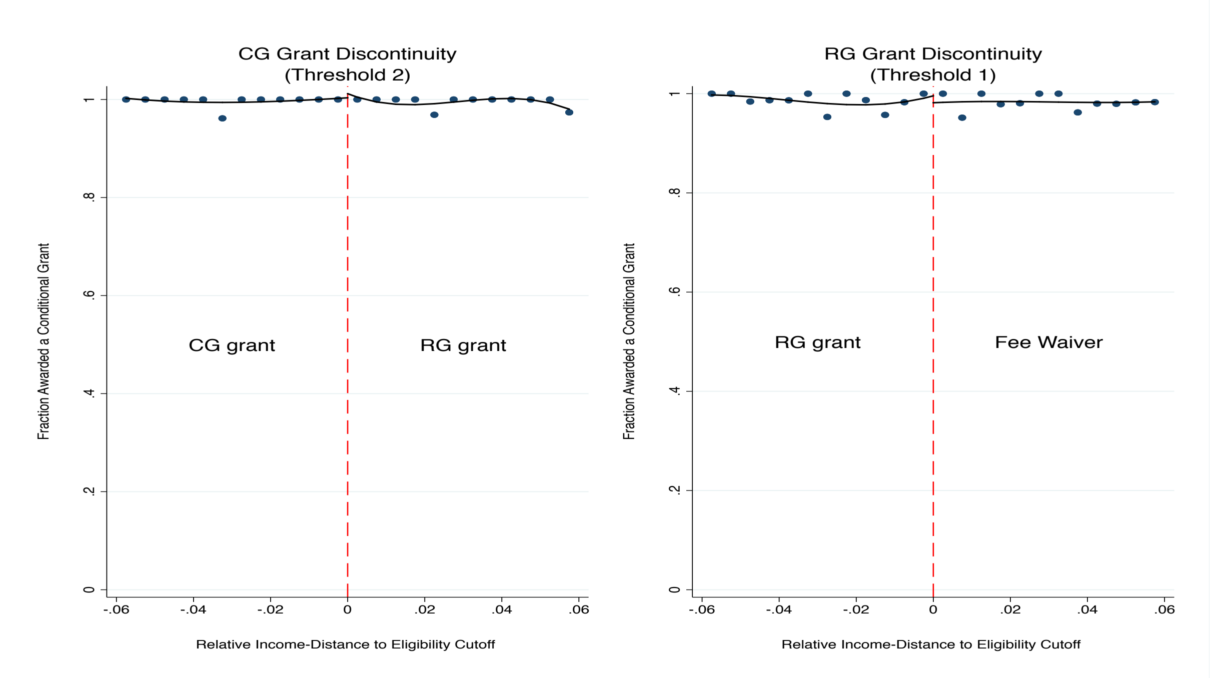
Notes: The figure depicts family income thresholds for different number of household members in the period 2010–2015. Thresholds are exactly the same amounts over the six-year period. FW refers to the fee waiver grant (Threshold 0), RG to Threshold 1 endowment, and CG to Threshold 2 allowance.

Figure 3: McCrary (2008) test for 2010–2015



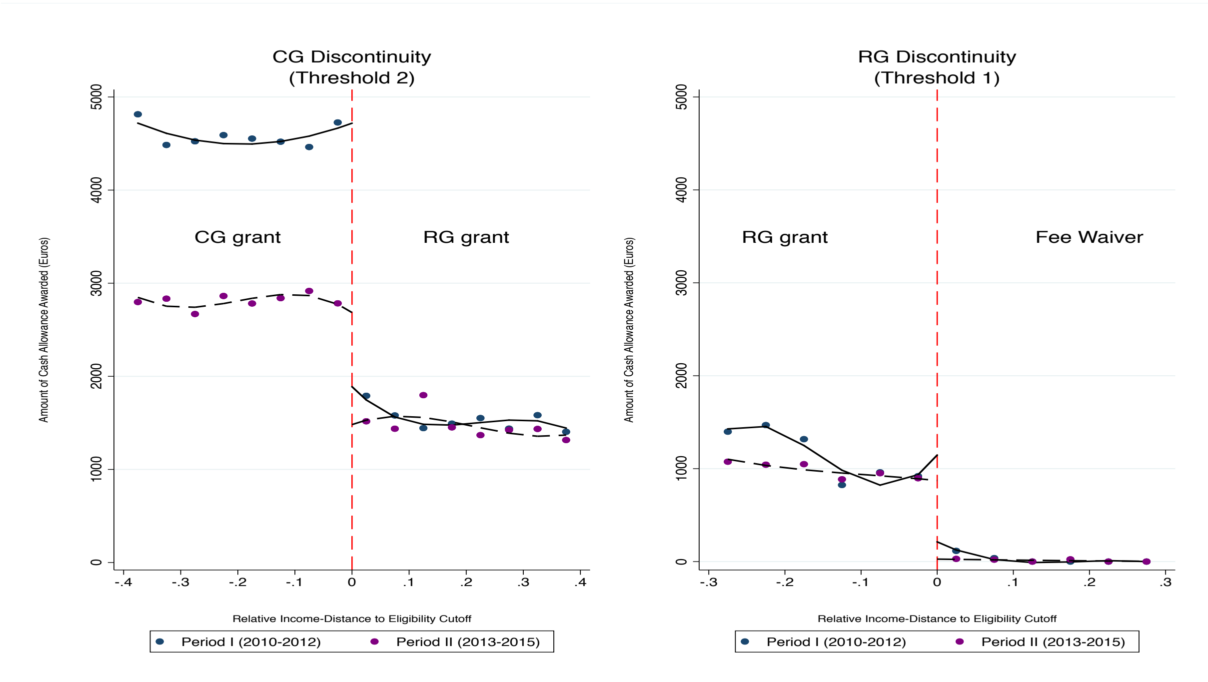
Notes: The figure shows the results of the test proposed by McCrary (2008). The weighted kernel density estimates are plotted, computed separately for each of the sides of the income thresholds RG and CG. The RG treatment sample includes applicants whose household parental taxable income is within 50 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 4: Fraction of Awarded a Conditional Grant for RG and CG (2010–2015).



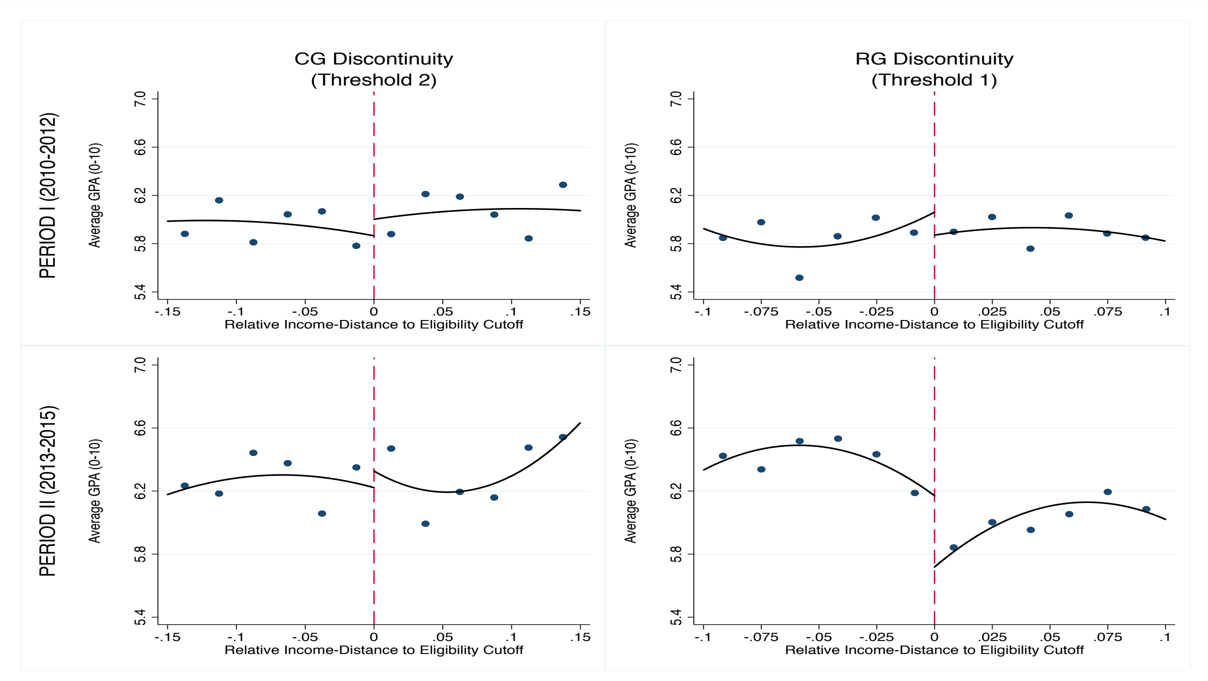
Notes: The dots represent the average fraction of applicants who were awarded a conditional grant per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "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 5: Average Grant Amounts for RG and CG by period.



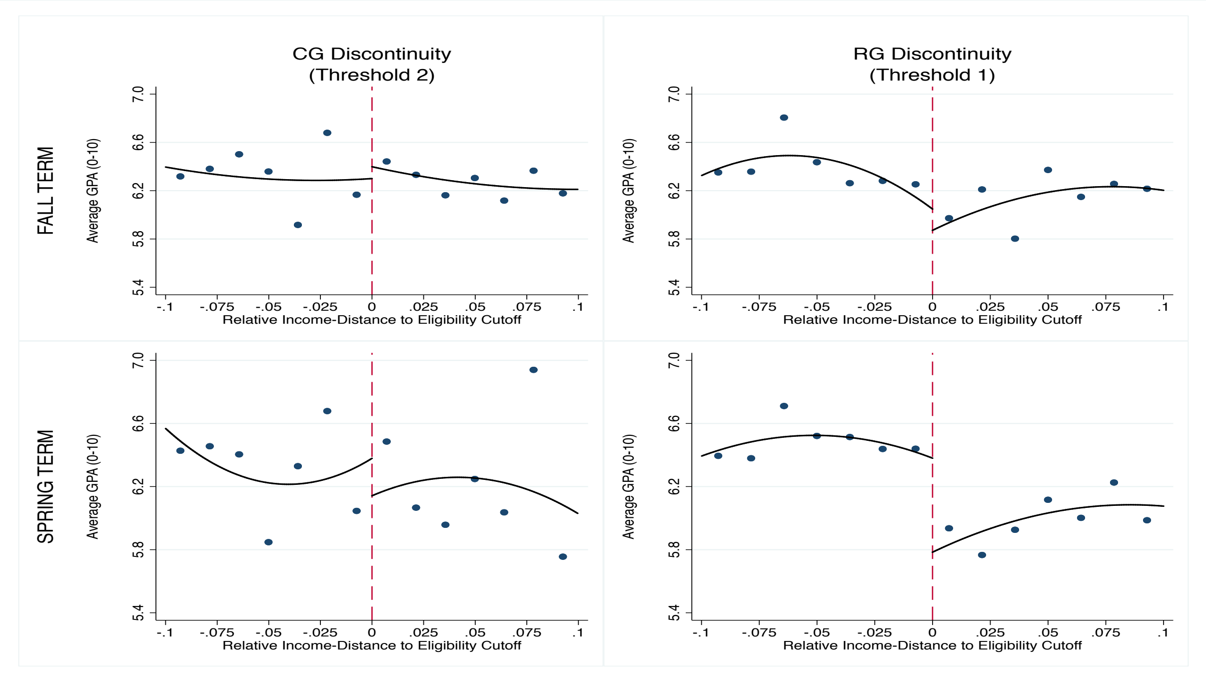
Notes: The dots represent the average grant amount per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility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

Figure 6: Average GPA (0-10) for RG and CG over Period I and II



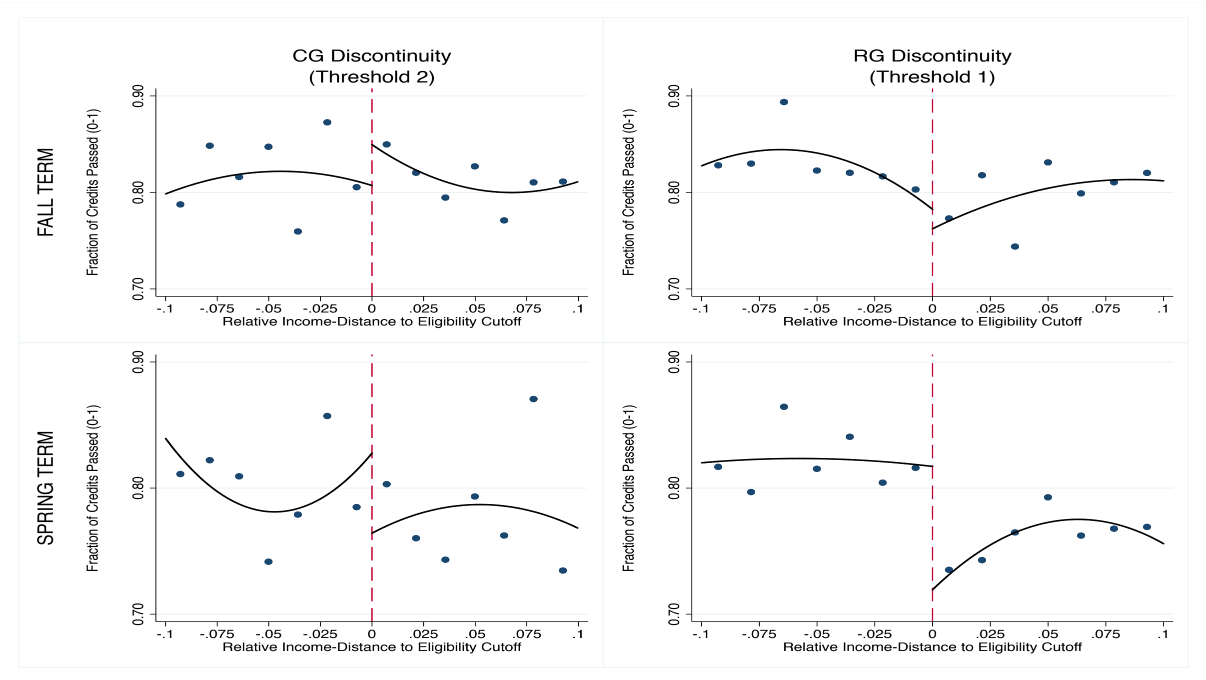
Notes: The dots represent the average grant amount per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility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

Figure 7: Average GPA (0-10) for RG and CG over Period I and II by Term



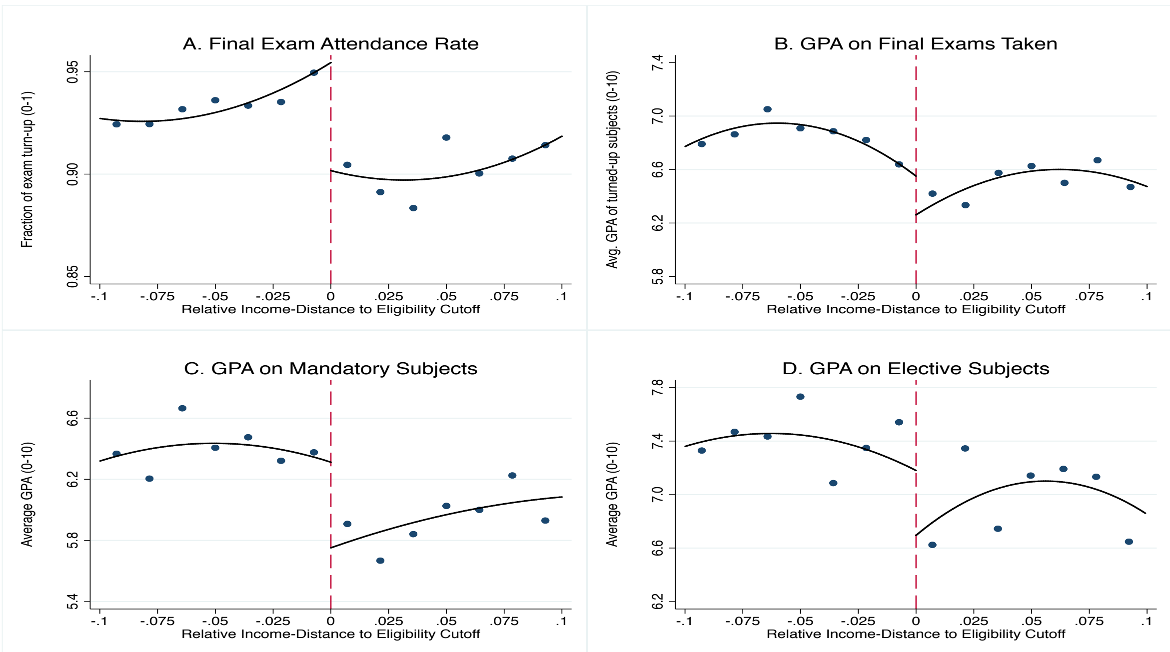
Notes: The dots represent the average grant amount per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility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

Figure 8: Fraction of Credits Passed (0-1) for RG and CG over Period I and II by Term



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 9: Mechanisms for Spring term at RG (2013–2015)



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.

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	2,745	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)	**CG grant** (Threshold 2) (1)	**RG grant** (Threshold 1) (2)
Applicants		
Female	0.48	0.47
Spanish	0.92	0.98
Access to University Percentile rank	52.40	55.40
	(28.60)	(28.46)
Technical degree	0.34	0.38
Applications		
Parent's taxable income (euros)	14,250	32,182
	(5,689)	(10,111)
# Family members	3.7	3.6
	(0.970)	(0.843)
% Disability	0.024	0.013
%Large family condition	0.17	0.11
Mover	0.32	0.28
Parental Occupation		
Entrepreneur	0.08	0.04
Blue Collar	0.44	0.3
Self-Employed	0.08	0.03
Conditional grant		
Awarded a conditional grant	0.99	0.72
Amount of Cash Allowance Awarded (Euros)	2,372	750.3
	(1,858)	(1,105)
Years		
2010	0.167	0.164
2011	0.171	0.168
2012	0.149	0.174
2013	0.164	0.162
2014	0.171	0.165
2015	0.178	0.167
N	6,835	10,050

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 away their family home" refers to the fraction of applicants who live away their 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 errors are in parenthesis.

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

Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
	Baseline mean (1)	Non-parametric Estimates (2)	Baseline mean (3)	Non-parametric Estimates (4)
A. Each baseline charcteristic separatelly				
Female	0.48	0.015	0.46	0.033
		(0.031)		(0.026)
		[6,951]		[11,965]
Spanish	0.94	-0.014	0.99	0.003
		(0.016)		(0.006)
		[6,951]		[11,965]
Access to University Percentile rank	53.41	-2.044	56.36	3.46**
		(1.858)		(1.594)
		[6,951]		[11,965]
STEM degree	0.35	0.004	0.41	-0.031
		(0.031)		(0.025)
		[6,951]		[11,965]
Households taxable income (euros)	17,282	-1.882	42,126	123.971
		(233.841)		(308.907)
		[6,951]		[11,965]
Disability	0.015	0.005	0.012	0.003
		(0.009)		(0.006)
		[6,951]		[11,965]
Large family condition	0.13	-0.000	0.13	0.007
		(0.024)		(0.020)
		[6,951]		[11,965]
#Family members	3.664	-0.004	3.651	-0.015
		(0.068)		(0.047)
		[6,951]		[11,965]
Live outside the family home	0.3	0.006	0.3	0.023
		(0.028)		(0.023)
		[6,951]		[11,965]
Entrepreneur Parent	0.073	0.007	0.04	-0.008
		(0.017)		(0.009)
		[6,951]		[11,965]
Blue Collar Parent	0.45	0.019	0.22	-0.041**
		(0.032)		(0.020)
		[6,951]		[11,965]
Self-Employed Parent	0.061	0.026	0.021	-0.003
		(0.017)		(0.008)
		[6,951]		[11,965]
# Awarded Grants	0.061	-0.107	0.37	-0.020
		(0.097)		(0.061)
		[6,951]		[11,965]
B. All baseline charcteristic jointly				
X2-stat		5.92		19.75
P-value		0.92		0.07

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 (2012) 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 away their family home" refers to the fraction of applicants who live away their 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. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Discontinuities in Allowance Amounts, GPA and Fraction of Credits Passed at Different Income Eligibility Thresholds and Periods.

Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)	**Period I** (2010-2012)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(1)	(2)	(3)	(4)
A. Average Allowance Amounts (euros)				
Non-parametric Estimates	2,955***	1,240***	675***	825***
	(147.657)	(108.270)	(98.806)	(37.662)
	[3,402]	[3,549]	[6,095]	[5,87]
Baseline mean	1,481	1,415	25.89	10.81
B. Average GPA (0-10)				
Non-parametric Estimates	-0.092	0.057	-0.031	0.455***
	(0.190)	(0.157)	(0.124)	(0.144)
	[3402]	[3549]	[6093]	[5868]
Baseline mean	5.97	6.29	5.91	6.15
C. Fraction of Credits Passed (0-1)				
Non-parametric Estimates	-0.017	0.016	0.006	0.059***
	(0.028)	(0.026)	(0.020)	(0.021)
	[3402]	[3549]	[6093]	[5868]
Baseline mean	0.78	0.80	0.77	0.79
D. Average Accumulated GPA over two years (0-10)				
Non-parametric Estimates	-0.017	-0.246	0.048	0.511**
	(0.197)	(0.170)	(0.124)	(0.205)
	[2,801]	[1,851]	[5,086]	[3,178]
Baseline mean	6.00	6.29	5.96	6.14
E. Fraction of passed credits accumulated over two years (0-1)				
Non-parametric Estimates	-0.008	0.021	0.025	0.063***
	(0.024)	(0.037)	(0.019)	(0.023)
	[2,806]	[1,86]	[5,088]	[3,184]
Baseline mean	0.85	0.86	0.85	0.85

Notes The table shows the RDD non-parametric estimates for the different applicants' average grant allowance received (Panel A), average GPA (Panel B), fraction of credits passed (Panel C) and average accumulated GPA over two years (Panel D). The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) 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. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Discontinuities in Average GPA and Fraction of Credits Passed at Different Income Eligibility Thresholds and Periods by Term.

Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)	**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)
A. Average GPA (0-1)				
A.1. Baseline Estimates				
Non-parametric Estimates	-0.092	0.057	-0.031	0.455***
	(0.190)	(0.157)	(0.124)	(0.144)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	5.97	6.29	5.91	6.15
A.2. First Term (Fall)				
Non-parametric Estimates	-0.024	0.020	0.030	0.282**
	(0.213)	(0.159)	(0.127)	(0.136)
	[3,299]	[3,470]	[5,904]	[5,703]
Baseline mean	6.01	6.33	5.91	6.20
A.3. Second Term (Spring)				
Non-parametric Estimates	-0.187	0.050	-0.118	0.560***
	(0.222)	(0.190)	(0.138)	(0.154)
	[3,282]	[3,400]	[5,885]	[5,600]
Baseline mean	6.02	6.33	5.99	6.19
B. Fraction of Credits Passed (0-1)				
B.1. Baseline Estimates				
Non-parametric Estimates	-0.017	0.016	0.006	0.059***
	(0.028)	(0.026)	(0.020)	(0.021)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	0.78	0.80	0.77	0.79
B.2. First Term (Fall)				
Non-parametric Estimates	-0.010	-0.003	0.018	0.037**
	(0.029)	(0.023)	(0.023)	(0.018)
	[3,299]	[3,470]	[5,904]	[5,703]
Baseline mean	0.79	0.82	0.77	0.80
B.3. Second Term (Spring)				
Non-parametric Estimates	-0.019	0.029	-0.012	0.073***
	(0.031)	(0.034)	(0.020)	(0.022)
	[3,282]	[3,400]	[5,885]	[5,600]
Baseline mean	0.78	0.80	0.78	0.79

Notes The table shows the RDD non-parametric estimates for the different applicants' average grant allowance received (Panel A), average GPA (Panel B), fraction of credits passed (Panel C) and average accumulated GPA over two years (Panel D). The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) 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. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Discontinuities in Official Dropout from higher education at RG and CG grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)	**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)
Non-parametric Estimates	0.007 (0.010) [3,402]	0.017 (0.014) [3,549]	0.020 (0.015) [6,095]	-0.014 (0.014) [5,87]
Baseline mean	0.019	0.02	0.03	0.03

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 (2012) 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 7: Discontinuities in Average GPA (0-10) at RG and CG grants by period and subgroup of applicants.

Treatment Sample: (Income Eligibility Thresholds)		**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)		**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)
A. By Gender					
A. By Gender					
Female	Non-parametric Estimates	-0.038	0.078	0.063	0.250
		(0.264)	(0.184)	(0.209)	(0.166)
		[1,644]	[1,689]	[2,879]	[2,735]
	Baseline mean	6.32	6.69	6.27	6.56
Male	Non-parametric Estimates	-0.167	-0.021	-0.110	0.465**
		(0.262)	(0.231)	(0.202)	(0.189)
		[1,758]	[1,859]	[3,209]	[3,132]
	Baseline mean	5.64	5.94	5.58	5.83
B. *PAU* entrance exam percentile rank					
Above Median	Non-parametric Estimates	-0.403	0.000	-0.179	0.523***
		(0.249)	(0.220)	(0.175)	(0.180)
		[1,838]	[1,772]	[3,433]	[3,254]
	Baseline mean	6.41	6.75	6.32	6.61
Below Median	Non-parametric Estimates	0.344	0.129	0.104	0.295
		(0.335)	(0.213)	(0.217)	(0.219)
		[1,484]	[1,722]	[2,504]	[2,516]
	Baseline mean	5.44	5.76	5.35	5.53
C. By residence status					
Living with parents	Non-parametric Estimates	0.044	-0.018	-0.083	0.450***
		(0.273)	(0.195)	(0.142)	(0.158)
		[2,346]	[2,388]	[4,417]	[4,11]
	Baseline mean	5.90	6.19	5.81	6.03
Living outside the family home	Non-parametric Estimates	-0.385	0.160	-0.045	0.524*
		(0.258)	(0.257)	(0.272)	(0.299)
		[1,056]	[1,16]	[1,671]	[1,757]
	Baseline mean	6.15	6.52	6.15	6.45

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 (2012) 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 away their family home" refers to the fraction of applicants who live away their 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.Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Discontinuities in the Fraction of Credits Passed (0-1) at RG and CG grants by period and subgroup of applicants.

Treatment Sample: (Income Eligibility Thresholds)		**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)		**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)
A. By Gender					
Female	Non-parametric Estimates	0.016 (0.038) [1,644]	0.008 (0.025) [1,689]	0.019 (0.026) [2,879]	0.039 (0.026) [2,735]
	Baseline mean	0.830	0.856	0.818	0.841
Male	Non-parametric Estimates	-0.063 (0.044) [1,758]	-0.006 (0.033) [1,859]	-0.004 (0.033) [3,209]	0.054** (0.027) [3,132]
	Baseline mean	0.730	0.760	0.726	0.744
B. *PAU* entrance exam percentile rank					
Above Median	Non-parametric Estimates	-0.058* (0.033) [1,838]	-0.019 (0.022) [1,772]	-0.004 (0.019) [3,433]	0.068*** (0.025) [3,254]
	Baseline mean	0.825	0.862	0.817	0.845
Below Median	Non-parametric Estimates	0.034 (0.051) [1,484]	0.029 (0.036) [1,722]	0.010 (0.035) [2,504]	0.032 (0.031) [2,516]
	Baseline mean	0.723	0.739	0.703	0.706
C. By residence status					
Living with parents	Non-parametric Estimates	0.004 (0.036) [2,346]	-0.012 (0.029) [2,388]	0.007 (0.025) [4,417]	0.058** (0.023) [4,110]
	Baseline mean	0.771	0.793	0.757	0.773
Living outside the family home	Non-parametric Estimates	-0.063 (0.045) [1,056]	0.044 (0.037) [1,160]	-0.007 (0.034) [1,671]	0.056 (0.039) [1,757]
	Baseline mean	0.799	0.830	0.798	0.822

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 (2012) 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 away their family home" refers to the fraction of applicants who live away their 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.Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Discontinuities for the mechanisms variables at RG and CG grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)	**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)
A. Final exam attendance rate (0-1)				
Non-parametric Estimates	-0.001 (0.016) [3,402]	0.006 (0.012) [3,549]	0.006 (0.012) [6,093]	0.032*** (0.010) [5,868]
Baseline mean	0.904	0.932	0.912	0.929
B. GPA on final exams taken (0-10)				
Non-parametric Estimates	-0.040 (0.156) [3,392]	0.074 (0.139) [3,541]	-0.049 (0.106) [6,077]	0.351*** (0.129) [5,859]
Baseline mean	6.512	6.699	6.396	6.552
C. Selection on courses (0-100)				
Non-parametric Estimates	0.097 (1.152) [3,402]	0.639 (1.164) [3,549]	2.117** (1.026) [6,093]	1.649* (0.935) [5,868]
Baseline mean	51.31	50.95	52.48	52.69
D. GPA on Mandatory Subjects (0-10)				
Non-parametric Estimates	-0.084 (0.200) [3,397]	0.107 (0.172) [3,548]	-0.050 (0.128) [6,089]	0.462*** (0.152) [5,865]
Baseline mean	5.908	6.210	5.868	6.103
E. GPA on Elective Subjects (0-10)				
Non-parametric Estimates	-0.689** (0.326) [1,298]	-0.056 (0.288) [1,288]	0.136 (0.205) [2,134]	0.553 (0.385) [1,924]
Baseline mean	6.954	7.370	6.802	7.236

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 (2012) 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. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Discontinuities in Degree Completion in Graduation Year at RG and CG grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)	**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)
Non-parametric Estimates	-0.1879	0.2251*	-0.1140	0.2713*
	(0.181)	(0.136)	(0.164)	(0.155)
	[548]	[640]	[915]	[1,065]
Baseline mean	0.395	0.394	0.421	0.367

Notes The table shows the RDD non-parametric estimates for the different applicants' degree completion. The treatment effect is estimated using a rectangular kernel and the bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) 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. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix to:

“The role of performance incentives in need-based grants for higher education: Evidence from the Spanish *Becas*”

(not intended for publication)

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The online appendix supplements the paper “The role of performance incentives in need-based grants for higher education: Evidence from the Spanish *Becas*”. It presents details on low-income students’ performance in higher education (section A), validity of the research design (section B), the discontinuities in BCG grants awarded to applicants (section C), the robustness of baseline estimates (section D), the comparability between Period I and Period II (section E), and the minimum academic requirements to being eligible for a BCG grant (section F).

A Low-Income Students' Performance in Higher Education

The analysis of the BCG grant is performed on low-income high school graduates enrolled in Carlos III University who applied to a BCG grant to start or to continue undergraduate college studies. To compare Carlos III students with the rest of collegian enrolled in the Spanish public universities, and more precisely, with the population of low-income students enrolled in higher education, I use data on student attainment in higher education provided by the Ministry of Education for the academic year 2014/2015. Dropout rates were computed for the cohort of students who enrolled Spanish higher education in the academic year 2010/2011 (which expected graduation from undergraduate program was 2013/2014 or 2014/2015).

The summary statistics presented in **Table A1** show substantial differences between Carlos III undergraduate students and their peers enrolled in the rest of the Spanish public higher education institutions. Students enrolled in Carlos III University scored higher in the standardized university access exam, reported higher graduation rates, passed a higher number of credits, and presented lower dropout rates. In contrast, BCG grant recipients in Carlos III are highly comparable to BCG grant recipients in Spain. These students reported similar GPAs, number of credits passed (over the total credits enrolled and the final exams taken), and time to graduation. The sample of grant applicants is reasonably representative of the general population of low-income students in Spain. These students can be considered as comparable to the typical targeted population of most large-scale need-based grant programs around the world, e.g students graduated from high school and admitted to college. The results cannot be directly generalized to the population of low-income students who fail in high school graduation and might respond differently to financial aid.

B Validity of the Research Design: McCrary (2008) Test

In order to perform a formal investigation of the validity of the research design, I test the non-random sorting of applicants at the income eligibility thresholds. I use the test proposed in McCrary (2008), which is a test based on an estimator for the discontinuity in the density function of the running variable at the cutoff, checking the non-systematic manipulation of household parental income around the thresholds.

The results of the McCrary (2008) test for Fee Waiver (FW) and Displacement and Other Needs Grant (DG) are presented in **Table B1**. McCrary test statistics confirm that the null hypothesis of no density jump at the eligibility cutoffs cannot be rejected for these income eligibility cutoffs. **Table B2** shows the results of McCrary (2008) test developed for all the different treatment samples used in this paper. Regardless of the treatment sample considered, the test statistic fails to reject the null hypothesis that the log difference in height around the discontinuity points is equal to zero. In addition, **Figure B1** displays the fraction of re-applicants and McCrary (2008) test for this sub-population of students. Applicants' who were awarded a grant in a given year might be more likely to reapply the next year, especially those below the cutoff of the RG grant. If it is the case, it may suggest that the impacts would be driven by this group of students, with no density break for applicants at the cutoffs but so for re-applicants. A robustness check testing the discontinuity in the density of re-applicants rejects this concern. Overall, these tests suggest that the probability of submitting an application does not change discontinuously at the income eligibility threshold, and thus applicants immediately above the cutoff are not able to manipulate their household parental income to being eligible for higher levels of grant.

C Discontinuities in Awarded Grants

This section test the different discontinuities of average awarded grants at the different income eligibility thresholds. **Table C1** presents the average allowance amounts (in constant euros of 2015) at RG and CG grants for the two periods studied and all the treatment samples used in the paper. This table shows that all the treatment groups present strong and statistically significant increments in average cash amount awarded at the discontinuity thresholds, except for students living with their parents when they enter university (non-movers) for RG grant at Period I. These subgroup of students were not eligible for financial aid at this specific threshold and period. **Table C2** shows the average cash amount at RG and CG grants for being eligible for a grant over two academic years. Conditional on applying for a grant at time t with a certain household income, it is possible to compute the average allowance amounts awarded over two years. This method would provide no sample selection concerns. However, the first stage decrease over time due to the variability of applicants' application status and household income over years. The discontinuities in the actual amount of conditional grant awarded to applicants are about 300 euros for RG grant on both periods, and similar estimates for CG grant but not statistically significant.

D Robustness Checks

In this section, I perform a number of tests in order to check the robustness of baseline estimates. Specifically, I i) investigate the sensitivity of estimates to the choice of bandwidth; ii) perform the local polynomial regression with robust bias-corrected confidence intervals proposed by Calonico, Cattaneo and Titiunik (2014); iii) run the baseline regressions adding student individual predetermined variables and year fixed effects; iv) test for jumps at non-discontinuity points by running placebo regressions.

D.1 Sensitivity to the Choice of Bandwidth

I analyze the sensitivity of the non-parametric estimates to the choice of the bandwidth and that changing the bandwidth size to half or twice the value of the optimal bandwidth proposed by Imbens and Kalyanaraman (2012). Panel B in **Table D1** shows that results are very similar to those obtained in the baseline estimates, but larger when using half the optimal bandwidth than double.

D.2 Local Polynomial Regression with Robust Bias-Corrected Confidence Intervals

To test for the variability of the results under local polynomial regression and a different computation for confidence intervals (robust bias-corrected) proposed by Calonico, Cattaneo and Titiunik (2014). Panel C in **Table D1** presents non-parametric estimates very close to the baseline.

D.3 Individual Control Variables and Year Fixed Effects

I investigate the volatility of baseline results when adding individual predetermined control variables (such as PAU percentile rank, gender, or being enrolled in a STEM degree) and year fixed effects that capture time trends in the outcome variable to the main regression. Panel D in **Table D1** shows that results are statistically significant at the 5 percent confidence level, but magnitudes is smaller than baseline estimates and similar to changing the bandwidth size to half of the optimal bandwidth proposed by Imbens and Kalyanaraman (2012).

D.4 Testing for Jumps at Non-Discontinuity Points

To test for jumps at non-discontinuity points, I run a placebo regression in which the income thresholds are artificially set at the midpoint between the actual eligibility thresholds by period. Since these midpoint do not correspond to any change in applicants' grant eligibility status, I should expect to find no significant jumps in average GPA. Panel E in **Table D1** presents that the points estimates are close to zero and non-significant in all specifications.

Overall, baseline results are robust to all different specifications and vary from an effect of 0.27 to 0.5 points, which corresponds to about 4.5 to 8.3 percent with respect to the baseline mean. Although the magnitude of estimates varies across specifications due to the limited sample size, the direction of the effects hold over the different specifications, indicating a robust impact of grant eligibility on student performance when the academic standards are strong. In addition, the null effect of the grant under the other different thresholds (CG and fee waiver grant) and periods is also robust and persistent for every sensitivity check performed.

D.5 Fee Waiver Grant (FW, Threshold 0)

The fee waiver is the first type of grant that students may receive, and covers the tuition fees but does not award with amounts of cash. This eligibility threshold (FW or Threshold 0) is very close to the eligibility cutoff the the RG grant. It makes difficult to construct two treatment samples between RG grant and fee waiver which do not overlap. The discontinuity induced by the tuition fee eligibility cutoff was ignored in the analysis, in order to focus on the grants types where students were awarded with cash amounts (in RG and CG grant).

As a robustness check, I have conducted a separate analysis of the treatment effect of being eligible for only tuition fee. **Table D2** reports the discontinuities in average cash amount awarded and average GPA. This table shows no evidence of statistically significant effects on awarded cash amounts and average GPA at this threshold.

D.6 Displacement and Other Needs Grant (DG, Threshold 3)

The heterogeneous effects (section 5) shows that the positive effects of being eligible for 760 euros on average relative to only fee waiver is only driven by non-movers. Those students received zero cash allowance in Period I, but 410 euros on average in Period II, while the effect is only statistically significant in Period II. Effects might be derived only by cash allowance award with no influence of performance-based incentives. In order to test the policy's efficiency, a deeper inquiry is needed to determine whether impacts are caused by the cash endowment, performance-incentive components, or the complementarity of both. As a robustness check, I use the DG grant for non-movers as comparison group for RG non-movers at Period I, since both thresholds are very close to each other. This analysis is useful to investigate the role of grant's performance-based incentive components.

The key advantages of using the DG cutoff are twofold. First, the DG grant is located 15 percent of the relative distance below the RG threshold, which mitigates concerns regarding the comparability of students in the vicinity of these two cutoffs.36 The sample of non-movers receives their first cash award at DG in Period I, which makes the comparable group similar to non-movers at RG in Period II. Second, the discontinuities in average cash grant amounts are very similar (543 vs. 410 euros). Hence, using non-movers in Period I for DG grant as a robustness check for RG non-movers in Period II is convenient due to the fact that it offers an scenario where entitlement to the grant, cash allowances and sample are comparable, but performance-incentives are different in the two periods.

Table D2 presents that the average discontinuity in cash allowance at DG in Period I is 543 euros for non-movers, and cash endowments at RG in Period II is 410 euros for non-movers. However, the null hypothesis of zero effect of being eligible for the DG grant on non-movers student performance cannot be rejected. Results are robust to different treatment sample sizes, regarding the predetermined characteristics of applicants (PAU percentile rank, gender, STEM degree, etc), year fixed effects, to set the optimal bandwidth proposed by Imbens and Kalyanaraman (2012) 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).[40]

This suggests that performance-based incentive components seems to play a crucial role on enhancing student achievement. Nevertheless, performance standards alone do not seem to be enough to improve student outcomes, since monetary incentives appear to be also crucial (there is no grant effect on fee waiver grant). The results point out to a complementarity between certain cash allowance and strong performance-based incentives as drivers of the effect of the grant on student performance.

[40] Results available upon request.

D.7 Differential effects on 2012

This section test for specific effects of the grant in 2012. The paper focus on the results on two periods, Period I and Period II. While academic incentives in Period II were homogeneous throughout the three academic years, Period II reported a change in 2012. Students had to passed 60 (80) percent of the credits attempted if the student was enrolled in STEM (non-STEM) degrees in 2010 and 2011. In 2012 the requirements rose to 65 (90) percent for students enrolled in STEM (non-STEM) degrees. **Table D3** presents the results of non-parametric estimates of being eligible for a need-based grant in this academic year. The null hypothesis of a null effect of the grant on student performance (average GPA and fraction of credits passed) and dropout cannot be rejected.

The results suggest that a single increase in the fraction of credits passed does not affect student performance. This points toward the direction of this paper's conclusion concerning the design of academic incentives. A performance standard framework with clear minimum thresholds targets combining minimum course loads and certain GPAs seems to be desirable in terms of the cost-effectiveness of the policy.

D.8 Student performance by academic term

The BCG's application process is described in section 2.2. Students are already enrolled at the higher education institution when they apply, and the vast majority of grant decisions are not notified before the end of the first term of the academic year. In addition, denied grants are disclose on average at the same time for both Period I and II, but conceded grants were divulged in February-March on average for Period I, and in June for Period II. This unique process may create an unclear view of when the grant incentives are created to improve student performance, due to the fact that students faced a different timing of acceptance/rejection disclosure. It is crucial to notice that student disclosure time is not a continuous variable, but rather discrete, since groups of students were receiving notification at the same time. An ideal way to test whether the effect of the grant on student performance was more powerful after the student received the notification is to compare the effect on students who received it before the term exams versus those who were informed after. Unfortunately, this sample split creates endogenous selection at the eligibility cutoffs, since denied grants were disclosed before accepted grants on average, arising to a break in the density at income thresholds.

A way to test this conjecture is to look at the impact of BCG grant on student performance by academic term (Fall and Spring). Students had a higher probability to get an answer on the second rather than on the first term. Then, it is reasonable to believe that student reaction to the allowance would be stronger for Spring than Fall grades. **Table D4** presents the non-parametric estimates by academic term, confirming this hypothesis. The size of grant effects are larger for the second than first term when testing the average GPA, and results for fraction of credits passed were not statistically significant for the Fall term, while in the Spring term were larger than the baseline results.

E Comparability between Period I and Period II

An important concern corresponds to the degree of comparability between applicants for a need-based grant in Period I and Period II. I test whether the students' observable characteristics of the comparison group at RG and CG grant in Period I are similar to applicants in Period II. I test the comparability of these students performing a t-test of the difference in observable characteristics between period. **Table E1** presents the results of this analysis. The null hypothesis of equality of the observable characteristics between periods cannot be rejected for three quarters of the variables at RG grant, and for more than half in CG grant.

F Academic requirements for BCG grant

This section summarizes the academic standards for being eligible for a BCG grant over the six-year period studied (2010–2015). In order to be eligible for a need-based grant, students must have complained with a minimum fraction of credits passed and average GPA the year before application. **Table F1** shows a summary of the different performance standards required by year, degree and cohort. It is remarkable the increase in the fraction of credits passed required in 2012, and the posterior change of the entire framework of academic incentives in 2013, which incorporates the average GPA of the year before application plus a variable component which depends on performance and family income the year of grant application (the variable component formula is described in **equation 11**). Figure displays a graphical summary of academic requirements for non-freshmen students. Academic incentives varied between the two periods:

- *Period I (2010–2012)*: incentives were based on the fraction of credits passed the year before application.

- *Period II (2013–2015)*: academic standards were based on the fraction of credits passed the year before application, the average GPA the year before application and in the application year (through the grant's individual variable component).

Table Appendix A1: BCG grant academic requirements.

	All Students			**BCG Grant Recipients**			**Non BCG Grant Recipients**		
	Spain (1)	Carlos III (2)	Diff. (2)-(1)	Spain (3)	Carlos III (4)	Diff. (4)-(3)	Spain (5)	Carlos III (6)	Diff. (6)-(5)
Avg. *PAU* score	8,5	10,29	1,79	8,67	10,28	1,61	8,76	10,51	1,75
Avg. GPA of enrolled students	7,24	6,95	-0,29	7,3	7	-0,3	7,2	6,9	-0,3
Number of credits passed over total enrolled	92,8	90,2	-2,6	88	88,6	0,6	74,9	82,3	7,4
Number of credits passed over total final exam taken	94,9	93,3	-1,6	92,1	93	0,9	84,9	89,7	4,8
Avg. time to graduation (4-year program)	4,4	4,8	0,4	4,4	4,8	0,4	4,5	4,8	0,3
Graduation rate (graduates in 2014/ total enrolled)	15,9	20,3	4,4						
Dropout rate (cohort 2010/2011)	28,42	24,7	-3,72	25,6	28,8	3,2	29,1	23,7	-5,4
# Enrolled	1,187,976	15,394		326,693	2,879		861,283	12,515	

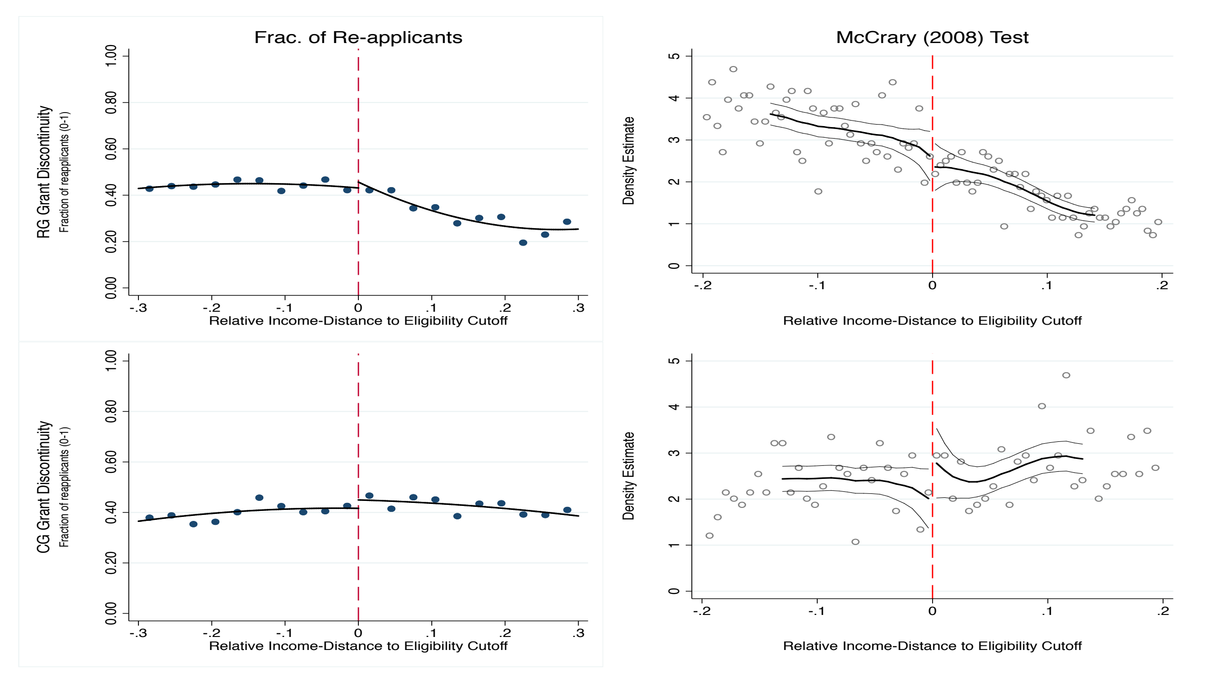
Notes

Table Appendix B1: McCrary (2008) Test for Manipulation of the Forcing Variable for Different Treatment Samples in FW and DG grant.

Treatment sample (Income Eligibility Thresholds)		**Fee Waiver Grant (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)		**Displacement and Other Needs Grant (DG) (Threshold 3)**			
		Log Difference in frequency bins (5)	**Z-stat** (6)	**Bandwidth** (7)	**Bin size** (8)
A. Total sample					
	Period I (2010-2012)	-.02 (.12)	.23	.09	.004
	Period II (2013-2015)	.09 (.15)	.62	.06	.004
B. By residence condition					
Living with parents	Period I (2010-2012)	-.12 (.17)	.69	.06	.005
	Period II (2013-2015)	.26 (.17)	1.49	.06	.005
Living outside the family home	Period I (2010-2012)	-.07 (.29)	.23	.05	.008
	Period II (2013-2015)	-.42 (.29)	1.43	.06	.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 away their family home" refers to the fraction of applicants who live away their family home, measured by the student' postal code when they access higher education. Standard deviations are in parenthesis.$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure Appendix B1: 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.

Table Appendix B2: McCrary (2008) Test for Manipulation of the Forcing Variable for Different Treatment subamples.

Treatment sample (Income Eligibility Thresholds)		**CG grant (Threshold 2)**				**RG grant (Threshold 1)**			
		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)	.13 (.22)	.60	.06	.006	-.079 (.12)	.647	.10	.004
Total Applicants	Period II (2013-2015)	.18 (.23)	.79	.07	.006	-.107 (.13)	.80	.10	.004
B. By Gender									
Females	Period I (2010-2012)	-.14 (.43)	.33	.05	.009	-.06 (.17)	.34	.096	.006
	Period II (2013-2015)	.29 (.36)	.81	.05	.009	.004 (.23)	.02	.072	.006
Males	Period I (2010-2012)	.16 (.25)	.61	.07	.009	-.11 (.2)	.55	.074	.006
	Period II (2013-2015)	.18 (.36)	.49	.06	.008	-.03 (.18)	.16	.10	.006
C. By PAU Percentile Rank									
Above Median	Period I (2010-2012)	-.05 (.27)	.19	.07	.008	-.14 (.19)	.75	.07	.005
	Period II (2013-2015)	.05 (.28)	.17	.07	.008	-.096 (.19)	.48	.08	.005
Below Median	Period I (2010-2012)	.28 (.34)	.83	.07	.01	-.016 (.24)	.07	.06	.007
	Period II (2013-2015)	.20 (.43)	.47	.06	.009	-.016 (.22)	.07	.08	.007
D. By residence condition									
Living with parents	Period I (2010-2012)	.12 (.26)	.45	.07	.007	.075 (.14)	.52	.09	.005
	Period II (2013-2015)	-.11 (.29)	.39	.07	.007	.054 (.16)	.32	.09	.005
Living outside the family home	Period I (2010-2012)	.14 (.38)	.38	.07	.012	-.65 (.37)	1.76	.059	.008
	Period II (2013-2015)	.62 (.33)	1.87	.09	.01	-.46 (.29)	1.56	.078	.008

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 away their family home" refers to the fraction of applicants who live away their 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.$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table Appendix C1: Average Allowance Amounts (in euros) at RG and CG grants by period and subgroup sample.

Treatment Sample: (Income Eligibility Thresholds) **Period:** (academic years)		**CG grant** (Threshold 2) **Period I** (2010-2012) (1)	**CG grant** (Threshold 2) **Period II** (2013-2015) (2)	**RG grant** (Threshold 1) **Period I** (2010-2012) (3)	**RG grant** (Threshold 1) **Period II** (2013-2015) (4)
A. Total Applicants					
	Non-parametric Estimates	2,955*** (147.657) [3,402]	1,240*** (108.270) [3,549]	675*** (98.806) [6,095]	825*** (37.662) [5,87]
	Baseline mean	1,481	1,415	25.89	10.81
B. By Gender					
Female	Non-parametric Estimates	3,231*** (222.727) [1,644]	1,339*** (158.675) [1,689]	878*** (140.786) [2,881]	946*** (57.538) [2,735]
	Baseline mean	1,604	1,561	21.59	20.70
Male	Non-parametric Estimates	2,715*** (213.360) [1,758]	1,103*** (178.747) [1,859]	472*** (131.423) [3,209]	696*** (54.368) [3,134]
	Baseline mean	1,364	1,287	29.75	2.88
C. PAU entrance exam percentile rank					
Above Median	Non-parametric Estimates	2,773*** (254.429) [1,838]	1,372*** (160.635) [1,772]	895*** (152.250) [3,435]	1,029*** (73.145) [3,256]
	Baseline mean	1,728	1,741	33.19	12.90
Below Median	Non-parametric Estimates	2,985*** (205.623) [1,484]	1,124*** (168.346) [1,722]	454*** (125.301) [2,504]	607*** (71.740) [2,516]
	Baseline mean	1,149	1,045	16.69	8.348
D. By residence status					
Living with parents	Non-parametric Estimates	2,984*** (141.017) [2,346]	1,235*** (115.897) [2,388]	-13.324 (62.261) [4,419]	445*** (19.519) [4,110]
	Baseline mean	818.2	1,019	16.70	2.652
Living outside the family home	Non-parametric Estimates	2,599*** (227.727) [1,056]	1,320*** (257.033) [1,160]	2,858*** (187.492) [1,671]	1,673*** (87.784) [1,759]
	Baseline mean	3,123	2,281	47.47	30.42

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 (2012) 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 away their family home" refers to the fraction of applicants who live away their 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 Appendix C2: Discontinuities in Average Allowance Amounts at t+1 for RG and CG grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)	**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)
Non-parametric Estimates	394	405**	377**	406***
	(310.184)	(181.193)	(150.853)	(67.479)
	[1,039]	[1,08]	[1,861]	[1,87]
Baseline mean	1,926	1,784	231.6	156.2

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 (2012) 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 D1: Discontinuities in Average GPA at RG and CG grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)	**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)
A. Baseline Estimates				
Non-parametric Estimates	-0.092 (0.190) [3,402]	0.057 (0.157) [3,549]	-0.031 (0.124) [6,093]	0.455*** (0.144) [5,868]
Baseline mean	5.97	6.29	5.91	6.15
B. Sensitivity Analysis				
B. 1 Half of the optimal bandwidth				
Non-parametric Estimates	-0.131 (0.270) [3,402]	0.087 (0.223) [3,549]	-0.054 (0.172) [6,093]	0.490** (0.201) [5,868]
Baseline mean	5.971	6.291	5.908	6.155
B. 2 Twice of the optimal bandwidth				
Non-parametric Estimates	-0.158 (0.150) [3,402]	0.013 (0.132) [3,549]	-0.021 (0.114) [6,093]	0.363*** (0.112) [5,868]
Baseline mean	5.971	6.291	5.908	6.155
C. RD Robust				
Non-parametric Estimates	-0.135 (0.274) [3,402]	0.088 (0.225) [3,549]	-0.001 (0.211) [6,093]	0.501** (0.201) [5,868]
Baseline mean	5.971	6.291	5.908	6.155
D. Baseline estimates with controls				
Non-parametric Estimates	-0.065 (0.154) [3,402]	0.013 (0.140) [3,549]	-0.159 (0.104) [6,093]	0.273** (0.124) [5,868]
Baseline mean	5.971	6.291	5.908	6.155
E. Placebo test with midpoint between RG and CG				
Non-parametric Estimates	0.0026 (0.120) [3,833]	0.1386 (0.136) [5,829]		
Baseline mean	5.990	6.327		

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 (2012) for each separated regression. Panel B displays the estimated treatment effect for half and twice the optimal bandwidth proposed by Imbens and Kalyanaraman (2012). 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 away their 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

Table D2: Discontinuities in Average Awarded Grant and Average GPA at Fee Waiver (FW) and Displacement and other needs grant (DG) by period.

Fee Waiver Grant (FW)

Treatment Sample: (Income Eligibility Thresholds)	**Avg. Awarded Grant (euros)** (Threshold 0)		**Avg. GPA (0-10)** (Threshold 0)	
Period: (academic years)	**Period I** (2010-2012)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(1)	(2)	(3)	(4)
A. Baseline Estimates				
Non-parametric Estimates	143*	-75.927	0.146	-0.235
	(75.273)	(50.125)	(0.189)	(0.272)
	[1,787]	[1,714]	[1,787]	[1,713]
Baseline	0.210	13.99	5.852	6.188

Displacement and Other Needs Grant (DG)

Treatment Sample: (Income Eligibility Thresholds)	**Avg. Awarded Grant (euros)** (Threshold 3)		**Avg. GPA (0-10)** (Threshold 3)	
Period: (academic years)	**Period I** (2010-2012)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(5)	(6)	(7)	(8)
A. Total Sample				
Non-parametric Estimates	730***	123	0.115	0.149
	(137.186)	(89.571)	(0.182)	(0.168)
	[3,936]	[3,909]	[3,935]	[3,907]
Baseline mean	662.2	673.9	5.853	6.250
B. By residence status				
Living with parents	693***	56	0.200	0.172
Non-parametric Estimates	(45.053)	(48.702)	(0.238)	(0.193)
	[2,896]	[2,724]	[2,895]	[2,724]
	98.90	394.1	5.748	6.154
Baseline mean				
Living outside the family home				
Non-parametric Estimates	888***	-240.677	0.095	-0.014
	(309.610)	(183.962)	(0.346)	(0.320)
	[1,037]	[1,184]	[1,037]	[1,182]
Baseline mean	2,303	1,342	6.138	6.480

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 (2012) 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 away their family home" refers to the fraction of applicants who live away their 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 D3: Discontinuities in Average Awarded Grant, Average GPA, Fraction of Credits Passed and Dropout at Residence Grant and Compensate Grant in 2012.

Treatment Sample: (Income Eligibility Threshold)	**CG grant** (Threshold 1) (1)	**RG grant** (Threshold 2) (2)
A. Average Allowance Amounts (euros)		
Non-parametric Estimates	2,792*** (213.989) [1,035]	657*** (141.691) [2,038]
Baseline mean	1,461	14.20
B. Average GPA (0-10)		
Non-parametric Estimates	-0.660 (0.401) [1,035]	-0.392 (0.298) [2,037]
Baseline mean	6.28	5.98
C. Fraction of Credits Passed (0-1)		
Non-parametric Estimates	-0.078 (0.054) [1,035]	0.017 (0.029) [2,037]
Baseline mean	0.81	0.77
E. Dropout from higher education		
Non-parametric Estimates	0.013 (0.011) [1,035]	-0.000 (0.010) [2,038]
Baseline mean	0.02	0.02

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 (2012) for each separated regression. Baseline mean refers to the average variable value above the eligibility threshold. 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 D4: Discontinuities for the mechanisms variables at RG and CG grants by period and term.

	First Term (Fall)				**Second Term (Spring)**			
Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)		**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
Period: (academic years)	**Period I** (2010-2012)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)	**Period I** (2010-2012)	**Period II** (2013-2015)
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
A. Final exam attendance rate								
Non-parametric Estimates	-0.001	-0.004	0.014	0.022***	-0.014	0.018	-0.004	0.046***
	(0.015)	(0.010)	(0.012)	(0.008)	(0.016)	(0.019)	(0.013)	(0.015)
	[3,299]	[3,47]	[5,904]	[5,703]	[3,282]	[3,4]	[5,885]	[5,6]
Baseline mean	0.916	0.947	0.920	0.941	0.901	0.921	0.911	0.922
B. GPA on final exams taken								
Non-parametric Estimates	-0.005	0.081	-0.033	0.185	-0.070	-0.007	-0.100	0.345***
	(0.151)	(0.146)	(0.105)	(0.116)	(0.168)	(0.136)	(0.107)	(0.117)
	[3,288]	[3,461]	[5,881]	[5,693]	[3,253]	[3,343]	[5,815]	[5,545]
Baseline mean	6.482	6.631	6.349	6.541	6.564	6.811	6.485	6.610
C. Selection on courses								
Non-parametric Estimates	0.333	0.623	2.288**	1.427	1.504	0.541	2.499**	1.683*
	(1.363)	(1.293)	(1.136)	(0.992)	(1.663)	(1.504)	(1.184)	(1.006)
	[3,299]	[3,47]	[5,904]	[5,703]	[3,282]	[3,4]	[5,885]	[5,6]
Baseline mean	51.57	51.06	52.56	53.51	51.37	50.90	53.13	53.40
D. GPA on Mandatory Subjects								
Non-parametric Estimates	-0.058	0.041	0.086	0.293**	-0.149	0.122	-0.183	0.491***
	(0.208)	(0.160)	(0.158)	(0.140)	(0.223)	(0.205)	(0.146)	(0.155)
	[3,274]	[3,426]	[5,865]	[5,628]	[3,261]	[3,374]	[5,85]	[5,57]
Baseline mean	5.961	6.281	5.868	6.160	5.942	6.227	5.954	6.122
E. GPA on Elective Subjects								
Non-parametric Estimates	0.089	-0.650*	0.055	-0.210	-1.136***	0.312	0.089	0.516
	(0.381)	(0.391)	(0.306)	(0.303)	(0.396)	(0.355)	(0.262)	(0.333)
	[1,065]	[1,038]	[1,693]	[1,48]	[1,101]	[1,021]	[1,777]	[1,509]
Baseline mean	7.077	7.451	6.992	7.394	7.029	7.381	6.875	7.230

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 (2012) for each separated regression. Baseline mean refers to the average variable value above the eligibility threshold. 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 E1: Difference in Baseline Means by period and treatment sample.

Treatment Sample: (Income Eligibility Thresholds)	**CG grant** (Threshold 2)		**RG grant** (Threshold 1)	
	Baseline Mean PI (1)	Difference PI vs. PII (2)	Baseline Mean PI (3)	Difference PI vs. PII (4)
Female	.49	.017 (.012)	.47	.025 (.0091)
Spanish	.95	.014** (.006)	.99	-.023 (.0027)
Access to University Percentile rank	54.57	2.27*** (.692)	56.54	.38 (.527)
STEM degree	.34	-.02 (.011)	.40	-.025 (.009)
Households taxable income (euros)	17,959	1,336*** (136)	43,703	3,306*** (187)
Number of family members	3.7	.0074 (.0234)	3.7	.042 (.016)
Disability	.011	-.007 (.0037)	.014	.005 (.0022)
Large family condition	.12	-.016* (.009)	.13	.012 (.006)
Live outside the family home	.29	-.027 (.011)	.3	.005*** (.0083)
Entrepreneur Parent	.07	-.005*** (.006)	.04	.003 (.004)
Blue Collar Parent	.42	-.05*** (.012)	.2	-.034** (.008)
Self-Employed Parent	.064	.004 (.006)	.023	.0044 (.003)
Awarded Grants	1	-.013 (.026)	.41	.088 (.019)

Notes The table shows a t–test for the differences in baseline means on different applicants' observable variables. 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 away their family home" refers to the fraction of applicants who live away their 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

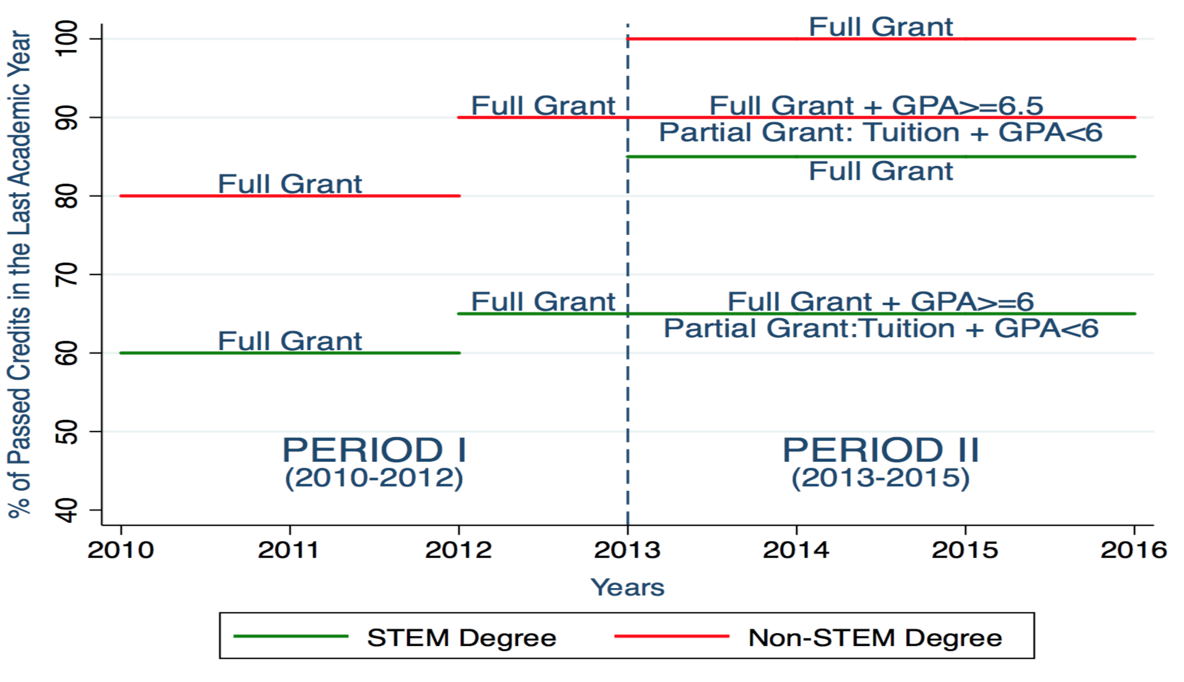
Table F1: BCG grant academic requirements.

A. Non-First year students					
	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	65%	90%	None	None	All
2013 onward	85%	100%	None	None	All
	65%	90%	>=6	>=6.5	All
	65%	90%	<6	<=6.5	Only Fee Waiver

B. First year students		
	Average Grade in PAU	**Grant rights**
Before 2013	5/10	All
2013 onward	6.5/10	All
	5.5/10	Only Fee Waiver

Notes

Figure Appendix F1: BCG grant academic requirements for non-freshmen students.



Notes: STEM refers to degrees in science, technology, engineering and mathematics. Non-STEM refers to all degrees but STEM, which at Carlos III University are degrees in Humanities and Social Sciences. Full Grant refers to the possibility of receiving one of the three levels of grant (Fee Waiver, Residence or Compensate). Partial Grant indicate that students can only be awarded with Fee Waiver grant independently of their parental income.

Variable component formula.

$$C_j = C_{min} + \left[(C_{total} - S * C_{min}) * \frac{(N_j/N_{max} * (1 - (\frac{R_j}{R_{max}}))}{\sum_{i=1}^{S}(N_i/N_{max}) * (1 - (\frac{R_i}{R_{max}})} \right] \tag{11}$$

where C_j= variable component amount that student j receives; C_{min} = minimum variable component; C_{total} = total amount of variable component to distribute among grant's recipients (depend on the year); S= number of applicants who receive variable component; N_j= applicant's average GPA; N_i = average GPA of each applicant to which S refers; N_{max}: average GPA obtained by the best decile of the same degree; R_j= applicant's income per capita; R_i = income per capita of each applicant to which S refers; R_{max} = maximum income per capita to be awarded with variable component (Threshold 1).