Countering moral hazard in higher education: The role of performance incentives in need-based grants*

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October 2018

Abstract

Large-scale financial aid programs targeted at disadvantaged students are generally tied to weak performance requirements for renewal. This may raise moral hazard concerns and efficiency losses. Using a reform in the Spanish need-based grant program in higher education, this paper tests the causal effect of receiving the same amount of grant under different intensities of academic requirements (i.e., having passed a certain number of credits) on student performance and degree completion. I use administrative micro-data on the universe of applicants to the grant in a large Spanish university. Exploiting sharp discontinuities in the grant eligibility formula, I find strong positive effects of being eligible for a grant on student performance when combined with demanding academic requirements. Students enhance their final exams attendance rate, their average GPA in final exams, their probability of completing a degree, and reduce the fraction of subjects that they have to retake. In contrast, the grant has no effects on student performance when academic requirements are low and typically comparable to those set out by national need-based student aid programs around the world. Overall, these results suggest that academic requirements in the context of higher education financial aid, may be an effective tool to help overcoming moral hazard concerns and improve aid effectiveness.

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

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

*I would like to especially thank Julien Grenet for his excellent, devoted and generous advice. I would like to express my gratitude to Ghazala Azmat, José E. Boscá, Antonio Cabrales, Natalie Cox, Gabrielle Fack, Javier Ferri, Martín Fernández-Sánchez, Martín García, Jesús Gonzalo, Marc Gurgand, Xavier Jaravel, Juan Francisco Jimeno, Clara Martínez-Toledano, Sandra McNally, Guy Michaels, Chrstopher A. Neilson, Fanny Landaud, Michele Pellizzari, Steve Pischke, Olmo Silva, Daniel Reck, Mariona Segú, Alessandro Tondini, Carmen Villa Llera and Ernesto Villanueva for their useful and wise comments. I am also grateful to Paloma Arnaiz Tovar, Gloria del Rey Gutiérrez, Luis Losada Romo and Elena Zamarro Parra, for their invaluable help in collecting the data. I thank seminar participants at Paris School of Economics, London School of Economics, University College London, Queen Mary University, Bank of Spain and European University Institute, as well as conference participants at the EEA-ESEM 2018, IZA World Labor Conference 2018, EALE 2018, IWAEE 2018, 16th "Brucchi Luchino" Labor Economics Workshop, XXVI AEDE Meeting, VIII Workshop on Economics of Education and Impact of Grants on Education and Research Seminar at AIReF. Finally, I am thankful to Fundación Ramón Areces and Bank of Spain for its financial support. An earlier version of this work was circulated under the title: "The role of performance incentives in need-based grants for higher education: Evidence from the Spanish *Becas*."

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1 Introduction

To make post-secondary education more accessible for disadvantaged students, many countries have implemented different policies, such as affirmative action programs, differential tuition fees rates or financial aid (e.g., grants or loans). Financial incentives that are not attached to performance for renewal may encourage enrollment and persistence of students who underperform in college, and who eventually may not be able to graduate, creating moral hazard concerns.[1] Introducing instruments of student accountability, such as grants linked to minimum academic requirements to renew them (i.e., having passed a certain number of credits), can be serve as an effective tool to better monitor student effort and potentially align social and private incentives. However, while academic requirements may mitigate moral hazard concerns by helping students to reduce failure rates on exams and time to graduation, they can have the unintended side effect of inducing some students to drop out. There is currently a controversial debate on whether these requirements improve the effectiveness of large-scale financial aid national programs. What makes this issue particularly policy relevant is that large-scale financial aid cover a large fraction of college students and represent a non-negligible share of the public budget. For instance, the US Pell Grant benefited over a third of college students and accounted for 18% of the total federal student aid in 2017/18 (Board, 2017).[2] Despite the relatively extensive literature on the effects of financial aid, it remains unclear to what extent grants tied to academic requirements are more effective than those without.

This paper investigates the causal effect of financial aid attached to minimum academic requirements on low-income students' academic performance and degree completion, using the Spanish large-scale need-based grant program. I exploit a national reform undertaken in 2013 that raised the academic requirements from a setting that is relatively comparable to those found in other national programs around the world (*weak* henceforth), such as the Satisfactory Academic Progress (SAP) in the US, to a more demanding one (*strong* henceforth).[3] I take

[1]This concern has been particularly vivid in the US, since college attendance rates have risen substantially, while undergraduate degree completion has been stable over the last two decades (Deming, 2017; Deming and Walters, 2017). This seems to be particularly salient for low-income students (Bailey et al., 2011).

[2]These programs typically provide fee waiver and award cash transfers to students based on their family income – other examples are the *Bourses sur critères sociaux* in France or the *Becas de Carácter General* in Spain. The debate regarding SAP has focused in the academic (Dynarski and Scott-Clayton, 2013; Goldrick-Rab et al., 2016; Patel and Rudd, 2012) and the public (Reauthorization (2013) and Gates Foundation's Reimagining Aid Design and Delivery project) sphere. Questions and concerns on financial aid policy are summarized in Scott-Clayton (2017*b*), and some of the proposals to change the Pell Grants are Baum and Scott-Clayton (2013) and Scott-Clayton (2017*a*).

[3]The SAP generally require students to maintain a GPA of 2.0 or higher, and to complete at least two thirds of the course credits they attempt for renew the Pell Grant (Scott-Clayton and Schudde, 2016).

advantage of this natural experiment to estimate the causal effect of financial aid under *weak* and *strong* academic requirements. There is a potential trade-off in tightening minimum academic requirements, that is analyzed based on a principal-agent model building on Bénabou and Tirole (2000) with academic standards (i.e., requirements), and financial aid (Scott-Clayton and Schudde, 2016). The model predicts that if the social planner increases the level of standards, some agents would become "more ambitious" exerting higher effort. However, the direction of the total effect is ambiguous, since some of the weaker agents types would "give up", exert zero effort and potentially drop out.[4] I exploit the extent of this trade-off using a Regression Discontinuity Design (RDD) that exploits the sharp discontinuities induced by family income eligibility thresholds, to estimate the impact of being eligible for different categories of allowances on student performance, degree completion and dropout from higher education. I take advantage of linked administrative micro-data, covering the universe of Carlos III University of Madrid students applying for the Spanish national grant program over the period 2010–2015. The dataset includes a comprehensive set of outcomes (e.g., GPA, dropout, final exam attendance or selection of courses). In a nutshell, I find that academic requirements turn out to be crucial, as their intensity plays an important role in stimulating low-income students' performance and degree completion, when combined with financial aid. In addition, I show that the increase in their stringency do not necessarily have an impact on student drop out from higher education.

One of the main challenges to identify the role that academic requirements play on the impact of financial aid on student performance, is that empirical evidence is usually only able to capture the combined impact of the awarded cash amounts and the impact of academic standards. Generally, the lack of reforms on the large-scale national programs and data availability, make difficult to address to what extent these requirements contribute to the total effect of financial aid.[5] Accordingly, previous empirical evidence presents limitations. Most of the existing literature focuses more on narrowly defined than in large-scale national programs, implemented in the

[4]Note that from the principal perspective, increasing standards would be worthwhile if the raise in the value due to those who are induced to exert higher effort overcomes the loss of value induced by those who shirk. When financial aid is incorporated to the model, Scott-Clayton and Schudde (2016) show that if the social value of those who shirk is lower than the value of financial aid, then aid with high standards seems to be unambiguously better than aid without. Nonetheless, the optimal line of standards and amount of financial aid that is socially optimal remains a question for future research.

[5]In a detailed summary of the lessons taken from the literature of financial aid, Dynarski and Scott-Clayton (2013) claim that "for students who have already decided to enroll, grants that link financial aid to academic achievement appear to boost college outcomes more than do grants with no strings attached". Recent papers have raised doubts on this statement, finding mixed evidence. Goldrick-Rab et al. (2016) find that grants with no strings seem to increase college persistence of low-income students using a randomized experiment in several public universities in Wisconsin.

US for a specific university or state (Deming and Dynarski, 2009; Dynarski and Scott-Clayton, 2013). Such programs are usually performance-based, which the vast majority of them are targeting high or medium achieving low-income students (Dynarski, 2008; Scott-Clayton, 2011), hence cannot be easily generalized to the population of low-income students. In addition, they often include additional components, such as academic and support services, which make difficult to isolate the precise role of academic requirements (Angrist, Lang and Oreopoulos, 2009; Angrist, Oreopoulos and Williams, 2014). The first contribution of this paper aims to fill this gap, by identifying how the impact for being eligible for equal grant amounts differ when combined with different intensities of academic standards. To my knowledge, this is the first paper that is able to isolate the specific contribution of academic requirements from the total effect of financial aid.

Another main obstacle to identification is the difficulty to isolate the impact of grants on the intensive margin response of student performance, since the vast majority of programs affect both the extensive and intensive margin simultaneously. Ex-ante, financial aid may induce new students to access college ("marginal" students), incentivizing enrollment. Average student performance may improve due to the increase in initial college enrollment, called the extensive margin. Ex-post, after enrollment, financial aid may enhance student performance of those students whose initial enrollment was not affected by the grant. This potential channel is the intensive margin (these students are referred as "inframarginal" students). The vast majority of the literature has focused on the extensive margin of enrollment, with several papers finding a statistically significant impact (Seftor and Turner, 2002; Fack and Grenet, 2015; Denning, Marx and Turner, 2017).[6] This makes difficult to interpret the intensive margin effect on performance due to the potential selection bias on those who access higher education.[7] Few papers have been able to isolate the effect of financial aid on the intensive margin (Murphy and Wyness, 2016; Goldrick-Rab et al., 2016; Denning, 2018). However, they cannot look at more comprehensive measures of student performance, such as fraction of subjects to retake or final exams attendance rate, since they mainly limit to graduation outcomes, earnings and college persistence. The second contribution of this paper stands on this challenge, by taking advantage of the specific timing of grant application in Spain to isolate the impact of the grant on the intensive margin of performance. In this unique framework, students are already enrolled in higher education when

[6] Empirical evidence looking at the Pell Grant aid program seems to be mixed, as several studies find no effect on college enrollment (Kane, 1995; Turner, 2017; Marx and Turner, 2018; Denning, 2018).

[7] 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 of all the population of college students, due to the fact that they focus on non-enrolled or freshmen students, who report the highest probability of dropout.

they apply for the grant, allowing to capture the effects on the intensive margin response, since the extensive margin is essentially muted due to the timing of grant applications.

The results show that being eligible for an average grant of 825 euros (relatively to being eligible for only fee waiver) under *strong* academic requirements increases student average GPA and fraction of credits earned by 0.45 points (on a 0 to 10 scale) and 6 percentage points respectively, which corresponds to an increase of approximately 7.3 and 7.6 percent with respect to the baseline mean. These effects corresponds to about 25 percent of the standard deviation of the dependent variable. The magnitudes of the effects are similar to those found for the West Virginia's PROMISE merit-based scholarship (Scott-Clayton, 2011), larger than those of Project STAR (Angrist, Lang and Oreopoulos, 2009) and slightly lower than Opportunity Knocks's (Angrist, Oreopoulos and Williams, 2014) merit-based experiments in a large Canadian university. Results are found to persist over time, enhancing the student cumulative average GPA and fraction of credits earned over two consecutive years, and increasing degree completion. In contrast, I find no effects of similar cash amounts in a regime of *weak* academic requirements. These results are consistent with papers finding limited effects of similar Pell Grant's cash amount on student GPA under a relatively similar context as the *weak* academic requirements setting (Denning, Marx and Turner, 2017; Denning, 2018). The baseline results are robust to an exhaustive number of specifications and sample selection criteria.

Interestingly, the effects do not seem to depend on the amount of financial aid awarded, as no further improvements in student performance are found for increments in the amount of awarded aid when students are already entitled to some positive amount of aid. The results suggest that student performance is mostly responsive to being awarded a grant with *strong* academic requirements, but consistent with the findings of Gneezy and Rustichini (2000), the boost in performance does not depend linearly on the amount received. In addition, I find that combine financial aid with *strong* academic requirements do not necessarily lead to an increase in drop out from higher education, which seems to contradict the findings of Scott-Clayton and Schudde (2016) in the US and Lindo, Sanders and Oreopoulos (2010) in Canada. The institutional context, especially the cost of college, may potentially be a relevant factor affecting the elasticity of dropout with respect to academic requirements.

This paper explores several possible mechanisms behind the results. The main ways in which financial aid may influence low-income students' performance are the cost-of-college and performance-incentives 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 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 the direction of the effects may be ambiguous if students lack the structural resources or knowledge to convert effort into a measurable achievement, or if financial rewards (or any kind of external reward) undermine intrinsic motivation and lead to negative outcomes.[8] I find that students are attending final exams more often, an indirect proxy of student effort. Students enhance their GPA on final exams taken, and reduce the fraction of subjects that they have to retake, which suggests a genuine increase in student performance. In addition, I investigate potential confounding factors that seem to rule out an increase in the probability of dropout from higher education and student selection of courses that may bias the baseline results. I am able to distinguish between subjects that are mandatory (i.e., those where students do not have room to self-selection) and elective (i.e., where students can choose a subset from a certain degree-specific set). The effect seems to be particularly robust for those courses which are compulsory, and hence cannot be avoided by students. Finally, I cannot test the cost-of-college channel directly in this paper, but I find that the student effort responds positively to being awarded some positive amount of aid combined with academic requirements, but the effort response seems unrelated to the amount awarded, a potential indirect evidence that may rule out this hypothesis.

Related literature. This paper is closely related to the literature on the effects of financial aid, in which relatively little is known about the effectiveness of large-scale need-based grant programs in enhancing low-income students' educational outcomes. Most of the existing literature focuses on the effects of need-based grants programs on college enrollment (Dynarski, 2003; Fack and Grenet, 2015; Castleman and Long, 2016), with fewer papers looking at other outcomes such as college persistence (Bettinger, 2004; Goldrick-Rab et al., 2016), graduation (Murphy and Wyness, 2016; Denning, 2018) and earnings (Angrist, 1993; Stanley, 2003; Denning, Marx and Turner, 2017). Existing studies have documented the positive influence of such programs on those low-income students' outcomes, specially for the sub-population of students who would not have entered university without financial support. Beyond the need-based programs, the vast majority of the literature has focused on merit-based grants that are awarded to students who meet certain

[8] See, for instance, Deci (1972), Kohn (1996) and Gneezy and Rustichini (2000) to observe some pieces of the extensive debate in psychology on whether extrinsic rewards crowd out intrinsic motivation.

academic requirements, and typically do not target low-income students.[9] These papers point out the importance of performance-based incentives on stimulating student performance, but effects seem to be small (Angrist, Lang and Oreopoulos, 2009; Angrist, Oreopoulos and Williams, 2014) and mixed.[10]

This paper is also related to the literature on how extrinsic incentives affect performance in the labor market (Lazear, 2000) and in non-employment contexts (Gneezy, Meier and Rey-Biel, 2011). In the latter, a number of studies have provided empirical support for the claim that stronger monetary incentives tend to lead to higher levels of effort, but the effect of monetary compensation on performance does not seem to be monotonic (Gneezy and Rustichini, 2000). 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). Empirical evidence that has evaluated extrinsic incentives from large-scale field experiments in educational contexts show that they increase attendance and enrollment, have mixed results on effort and achievement, and seem to work for some students but not for others (Gneezy, Meier and Rey-Biel, 2011). In addition, this paper also contributes to the literature on the effects of performance standards. There is a large literature that has examined the impact of academic standards in the educational context, especially in the form of high schools exit exams. Empirical evidence has focused on the effects of the presence of high school exit exams, and the impact of failing high school exams on dropout and performance, finding mixed results (Muller, 1997; Amrein and Berliner, 2002). In higher education, Lindo, Sanders and Oreopoulos (2010) examined the students' responses of being placed in academic probation at the end of the first year, showing that some students are discouraged to return to university while those who stay improve their GPAs. The authors highlight the potential trade-off between the increased effort and dropout, induced by the academic standards. However, it remains unclear to what extent results from these papers may be generalized to the case when extrinsic incentives and

[9]These grants have a long tradition in the US post-secondary system. Traditional programs such as the US National Merit program and Canadian Excellence Awards, were originally targeted to top-performers. In the 1990's, several programs as Georgia's Helping Outstanding Pupils Educationally (HOPE) were introduced for non-top students in different US states (e.g., Florida or Arkansas). Empirical evidence devoted to investigate the effects of the numerous HOPE-style programs have found positive results for key students' outcomes (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.

[10]The Manpower Demonstration Research Corporation (MDRC) has performed several randomized evaluations of performance-based scholarship (several of them targeted to low-income students) finding mixed results (e.g., Mayer et al. (2015), Barrow et al. (2014), Cha and Patel (2010), Miller et al. (2011), Richburg-Hayes et al. (2009) or Richburg-Hayes, Sommo and Welbeck (2011).

performance standards are combined. This paper contributes to these strands of the literature showing that combining financial aid and *strong* academic requirements has positive effects on student performance, while it does not necessarily lead to an increase in drop out, using a large-scale program targeted to low-income students.

Organization of the Paper. 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 shows a conceptual framework to describe the fundamental trade-offs involved in setting performance standards in need-based student aid. Section 4 describes the data used in the paper. Section 5 explains the empirical strategy. Section 6 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 7 discusses the external validity, efficiency and equity potential costs. Section 8 concludes.

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*),[11] which consist on two-year college preparation courses and a standardized entry exam (*Selectividad*).[12] If the demand for a specific program in the Spanish public universities 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.

[11] 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.

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

The cost of higher education in Spain is mainly composed of tuition fees and living expenses. Tuition costs vary depending on the region where the university is located, the degree program undertaken, and the repeated subjects failures. The national average tuition fees for a full academic year was 1,100 euros for undergraduate students in 2015 and between 1,634 and 2,347 euros for graduate students.[13] 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.[14] Furthermore, according to current estimations for the first semester of 2015, the average cost of living expenses in Spain for a nine-month period was 5,069 euros,[15] which represent a significant financial barrier to emancipate from their family home and to access higher education.

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 are the equality of opportunities and to improve educational efficiency by promoting low-income students' potential.

The program consists on three main levels of grant: (i) the Fee Waiver (Threshold 0) exempts 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 (T1 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 (T2 grant hereafter) requirements, the average amount in-

[13]Public prices are detailed in *Estadísticas de precios públicos universitarios del MECD*.
[14]See Ariño (2011).
[15]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*.

creases on an additional 3,000 euros (3,500 euros) for those who live in (away from) 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 (T3 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.[16] 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, which is based on the after–tax household income. Qualification for a grant and the amount awarded depend on the students' household taxable income, as well as the number of household members.[17] 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).[18] The grant can be denied 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 T1 grant), for a household with four members (which is the average size in the sample), the annual family

[16]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.*

[17]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.

[18]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.

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.[19] To be eligible to the highest level of grant (T2 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.[20]

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.
- *Mid November/December*: applications start to be answered for non-eligible students. Application outcomes are not necessarily disclosed at the same time for all applicants and answers are distributed along the academic year. Awarded and denied grants are notified in February–March of the academic year on average. 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. This is due to the fact that students are already enrolled in a 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 whether or not they receive financial support) and measure "intensive" rather than "extensive" margin responses.

The potential manipulation of information by applicants could be a concern for this type of allowances. It should be noted, however, that the authority handle in the grant applications di-

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

[20] 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.

rectly 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, thus complicating 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 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. Potential manipulation on eligibility threshold is discussed extensively in Section 5.1.

Changes to the BCG Grant: Period I vs. Period II. 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 frameworks. In 2013, academic requirements were modified and a variable component was included.[21]

First, in addition to the three main cash allowances, the framework in Period I included the T3 grant, which was based on a number of criteria such as distance to university, educational material, etc. In 2013, these different fixed amounts were merged into a single individual variable element, with conceded allowance if the student's family income was below the T1 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 in the year before application.[22] Therefore, the main difference across periods is the fact that students were receiving a large fixed amount of grant in Period II, and smaller fixed amount plus a variable allowance in Period II. Overall, the average amount of T1 grant was statistically the same across

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

[22] The exact formula of the variable component of the grant is provided in the online appendix (section H). 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*

periods, but it was lower in Period II than in Period I for T2 grant (discontinuities in average grant amounts are discussed extensively in Section 5).

Second, the academic requirements set to be eligible for a grant became more stringent in Period II. 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;[23] (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 non-STEM.
- *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 have obtained an average GPA of 6/10 (6.5/10) respectively for STEM (non-STEM) degree.

Overall, the changes between the two periods can be summarized as: (i) an increase in the minimum fraction of credits earned; (ii) the inclusion of the average GPA as a requirement; (iii) the incorporation of the grant's variable component which award students with different grant amounts depending on their GPAs. For simplicity, from now on I will refer to academic requirements in Period I as *weak*, and these of Period II as *strong*.[24]

3 Theoretical Framework

Bénabou and Tirole (2000) present a principal-agent model with standards (i.e. academic requirements) that is useful to rationalize the intuitions behind this paper. In the original model there are two tasks: low-effort task (Task 1) with private benefit to the agent V_1, effort cost c_1, and principal's benefit W_1; high-effort task (Task 2) with private benefit to the agent V_2, effort cost c_2, and principal's benefit W_2. In the context of this paper, low-effort task may be

[23] In Spain the GPA can take values between 0 (the minimum grade) and 10 (the maximum). 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+.

[24] A detailed summary of the policy change regarding academic performance requirements is provided in the online appendix, section H.

understood as *weak* academic requirements and high-effort task as *strong* academic requirements. Either task yields 0 to both subjects in case of failure such that:

$$0 < V_1 < V_2; 0 < W_1 < W_2; \text{ and } 0 < c_1 < c_2 \tag{1}$$

They further assume that:

$$\theta_1 \equiv \frac{c_1}{V_1} < \theta_2 \equiv \frac{c_2 - c_1}{V_2 - V_1} < 1 \tag{2}$$

The probability of success (θ) is the same in both tasks. They assume that the agent knows θ but the principal does not. The prior cumulative distribution of θ on $[0,1]$ is denoted as $F(\theta)$ with density $f(\theta)$. The agent solves:

$$\max \ \{0, \theta V_1 - c_1, \theta V_2 - c_2\} \tag{3}$$

The agent chooses to shirk if $0 \leq \theta < \theta_1 \equiv \frac{c_1}{V_1}$, task 1 if $\theta_1 \equiv \frac{c_1}{V_1} \leq \theta < \theta_2 \equiv \frac{c_2 - c_1}{V_2 - V_1}$, and task 2 if $\theta_2 \equiv \frac{c_2 - c_1}{V_2 - V_1} \leq \theta < 1$.

Suppose now that the principal forbids the low-effort task, such that the agent has to choose between shirking or doing the high-effort task. The intuition behind this action is that the principal increase the academic requirements from *weak* to *strong*. With this *strong* standards, the agent exerts effort if and only if:

$$\theta < \frac{c_2}{V_2} \equiv \theta^* \tag{4}$$

Notice that the standard make types in $[\theta^*, \theta_2]$ to exert the high-effort task/*strong* standards (*more ambitious*), but at the same time makes types in $[\theta_1, \theta^*]$ to shirk (*give up*). From the principal perspective, including *strong* standards would be worthwhile if the raise in the value due to those who are induced to exert higher effort overcome the loss of value induced by those who shirk:

$$S(\theta_1, \theta_2) = \left(\int_{\theta^*}^{\theta_2} \theta f(\theta) d\theta \right) (W_2 - W_1) - \left(\int_{\theta_1}^{\theta^*} \theta f(\theta) d\theta \right) W_1 > 0 \tag{5}$$

Scott-Clayton and Schudde (2016) analyze Bénabou and Tirole (2000) model introducing financial aid with and without standards, which may be comparable to financial aid with *weak* and *strong* academic standards in this context. The principal provides the agent with financial aid a, that is granted based on student enrollment and does not depend on other outcomes (i.e., it is available for agents who exert task 1 and task 2). It will end up with a new $\theta_1^a < \theta_1$, but $\theta_2^a = \theta_2$. The grant induces more individuals to task 1 but none additional agent to task 2. Thus, enrollment subsidies cannot lead to a social optimal outcome, but they may be desirable relative to no aid without standards if:

$$S(\theta_1^a, \theta_1) = \left(\int_{\theta_1^a}^{\theta_1} \theta f(\theta) d\theta \right) W_1 - \left(\int_{\theta_1}^{\bar{\theta}} f(\theta) d\theta \right) a > 0 \tag{6}$$

When adding academic standards, the principal forbid low-effort task, and the threshold for using high effort option declines to:

$$\frac{c_2 - a}{V_2} \equiv \theta^{*a} < \theta^* \tag{7}$$

This policy is worthwhile for the social planner relative to financial aid without standards if:

$$S(\theta^{*a}, \theta_1^a, \theta_2) = \left(\int_{\theta^{*a}}^{\theta_2} \theta f(\theta) d\theta \right) (W_2 - W_1) - \left(\int_{\theta_1^a}^{\theta^{*a}} (\theta W_1 - a) f(\theta) d\theta \right) > 0 \tag{8}$$

If the social value of forbidden low-effort is lower than the grant's value a, aid with performance standards is unambiguously better than aid without. Performance standards are always desirable when there is some level of low-effort that generates social value lower than a. Hence, the research question is *where to set the dividing line between the acceptable W_2 and the unacceptable W_1* (Scott-Clayton and Schudde, 2016). 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.

It seems that a minimum standard is desirable, but determining whether it is too high or rather low would require weighting the value of encouragement and discouragement effects. Along with these authors statements, the effects of an increase in the academic requirements would depend on four dimensions: the magnitude of a, the shape of the ability distribution, the relative benefits of task 2 versus task 1, and the relative benefits of task 1 versus shirk.

4 Data

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 contains 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, reason for denial and type of scholarship), and parent's occupation. The awarded grants database provide details about the BCG grant amounts, the type of allowance and the date of award. 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 have applied once or more 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 detailed information of each subject's course undertaken (final grade obtained, attendance of the final exam, retake, etc.).

Sample Restrictions. On average, 5,300 Carlos III students apply for a BCG 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 all applicants. Graduate students are not included in the analysis due to the small sample size. Moreover, I focus on students who were not denied the grant due to problems with the Tax Agency, were declared non-eligible due to excess wealth or business income, and meet with the minimum academic requirements in order to make the regression discontinuity design sharper.[25]

[25] Students excluded from the sample of analysis represented 25 percent of the total applicants over the six-year period covered by the study (16 percent corresponds to problems with the Tax Agency and exceed the wealth and business thresholds, and 9 percent for not meeting the academic criteria). 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). Moreover, discarding students who did not meet the minimum academic requirements do not change the statistical significance and magnitude of results (results available upon request).

5 Empirical Strategy and Conceptual Framework

5.1 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 T1 and T2 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}:

$$E_{i,k,t} = \mathbb{1}\{c_{it} \leq \bar{c_k}(m_{it})\} \tag{9}$$

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):

$$A_{it} = \mathbb{1}\{t \leq 2012\} * \sum_{k=1}^{2} \alpha_{k,1} E_{i,k,t} + \mathbb{1}\{t > 2012\} * \sum_{k=1}^{2} \alpha_{k,2} E_{i,k,t} \tag{10}$$

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

$$\alpha_{k,1} = \gamma_{k,1} \tag{11}$$

$$\alpha_{k,2} = \gamma_{k,2} + z_i(c_i, \overline{c_i}, g_i, \overline{g_i}) \tag{12}$$

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 the variable component granted to applicant i with household where income is c_i and grades are 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:

$$Y_{it} = \alpha + \mathbb{1}\{t \leq 2012\} * \sum_{k=1}^{2} \beta_{k,1} E_{i,k,t} + \mathbb{1}\{t > 2012\} * \sum_{k=1}^{2} \beta_{k,2} E_{i,k,t} + \epsilon_{it} \tag{13}$$

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 in the household income distribution. Absent 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:

$$\beta_{k,p} = \lim_{c \uparrow \bar{c_k}(m)} E[Y \mid c, m, p] - \lim_{c \downarrow \bar{c_k}(m)} E[Y \mid c, m, p] \tag{14}$$

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 T1 and T2 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[26]. I use the relative distance to the income-eligibility

[26] Note that the fee waiver eligibility threshold is close to the eligibility cutoff the the T1 grant (as observed in Figure 1) making difficult to construct two treatment samples (with sufficient number of observations) between

threshold as forcing variable.

The treatment samples are defined as follows: (i) The first sample combines the eleven household taxable income cutoffs of the T1 grant. In this sample, I identify the treatment effects $\beta_{1,1}$ and $\beta_{1,2}$ of being eligible for an approximate average cash allowance of 675 euros and 825 euros respectively (the difference is not statistically significant) in Period I and II, relatively to being eligible to fee waiver only. (ii) The second sample combines the eleven parental income thresholds of T2 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 2,955 euros and 1,240 euros respectively (the difference is statistically significant) in Period I and II, relative to being eligible for about 1,400 euros on average. Figure 2 shows the amount of annual cash amounts awarded to applicants with 4 family members as a function of their parents' taxable income across periods.

Notice that the treatment effects are measuring the causal effect of a change in the amount of grant on student performance under certain academic requirements:

- $\beta_{1,1}$ and $\beta_{1,2}$ measure the causal effect of equivalent change in the average grant amounts under weak and stronger academic requirements. The change in the cash amount is the same but interacted with two different levels of performance standards. Comparing both estimates I can investigate the direct effect of two different academic requirements holding constant the change in the cash amount awarded. The comparison group in both estimates is awarded with fee waiver.

- $\beta_{2,1}$ and $\beta_{2,2}$ measure the causal effect of different changes in the average grant amounts under weak and stronger academic requirements. The common factor between both parameters is the fact that the comparison group is already awarded with non-zero the baseline average grant (approximately 1,400 euros). However, the changes in the amount of grant (1,700 euros of difference) and academic requirements are different.

The treatment effects are estimated using a triangular kernel.[27] The standard errors are computed using standard least squares methods (robust standard errors) clustered at the stu-

T1 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.

[27]Results are robust to using a rectangular instead of a triangular kernel. Results are available upon request.

dent level.[28] The bandwidth is computed as the optimal bandwidth proposed by Imbens and Kalyanaraman (2012).[29]

Summary Statistics. Table 2 shows summary statistics on the sample of BCG grant applicants who are considered in the analysis. I split the estimation sample into two sub-groups: (i) the T1 grant sample (Threshold 1) includes applicants who are in the vicinity of the T1 grant threshold; (ii) the T2 grant sample (Threshold 2) includes applicants whose relative household income is close to the T2 grant threshold. Most of the applicants are Spanish, live 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 T1 grant sample, and approximately 14,000 euros for the T2 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 work as blue collars.

5.2 Conceptual Framework

This subsection provides a conceptual framework on the potential differential effects that grants may have on student performance under different cash amounts granted and academic requirements, given the individual income levels. The goal of this subsection is to provide intuitions on which parameters are estimated in this paper, and to rationalize the potential directions of the effects.

Let student performance (gpa) depends on the cash amount awarded (a), the performance standards required (s), and the individual income level (y):

$$gpa = f(a, s, y) \tag{15}$$

[28] 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.

[29] A potential concern with the RDD regards the presence of treated (untreated) students for complying (not meeting) the academic requirements on both sides of the income-eligibility thresholds. I perform a robustness check testing the significance of the baseline results on a treatment sample that include those students. The results are robust to this test and are available upon request. An alternative 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 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 earned 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.

where $f(.)$ is assumed to be a deterministic function.

Assume that performance standards can be either high ($\bar{s}$) or low ($\underline{s}$), and that grant amounts may take three values ($a_1 > a_0 > 0$). 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, $f_a(a, s, y) > 0$ and $f_s(a, s, y) > 0$.

Without loss of generality, define $\Delta gpa = f(a_1, s, y) - f(a_0, s, y)$, as the change in student performance under different levels of grant amounts (a_0, a_1). This equation can be written as a function of the partial derivatives using a Taylor expansion:

$$\Delta gpa = f(a_1, s, y) - f(a_0, s, y) \sim f_a(a_0, s, y) * (a_1 - a_0) \tag{16}$$

where a_0 denotes the amount of financial aid above a certain cutoff and a_1 the grant amount below the specific threshold. Intuitively, this can be interpreted as the performance differential effect of receiving a_1 level of financial aid, relative to obtaining a_0 (where $a_1 > a_0$).

There are four cases where amounts and performance standards differ, that may be rationalized for two scenarios that have different baseline amounts:

(i) $a_0 = 0$:

$$\Delta gpa = f(a_1, s, y) - f(0, s, y) \sim f_a(0, s, y) * a_1 \tag{17}$$

(ii) $a_0 > 0$:

$$\Delta gpa = f(a_1, s, c) - f(a_0, s, y) \sim f_a(a_0, s, y) * (a_1 - a_0) \tag{18}$$

where $s = \{\underline{s}, \bar{s}\}$.

Given an "s" type, the differences in performance differential effect (Δgpa) under the two scenarios (i) and (ii) would depend on two metrics: the difference between the marginal increase in the level of amount evaluated at level of grant zero vs. at certain positive amount a_0, and on the difference between the relative changes in the amount of grant – i.e. a_1 vs. $(a_1 - a_0)$. The distribution of derivatives with respect to a evaluated at different level of grants may be ambiguous. If the change in performance with respect to an infinitesimal increase in a is linear and constant throughout the amount of grant distribution implies that $f_a(0, s, y) \approx f_a(a_0, s, y)$. However, it may be the case that the change in performance is different throughout the amount of grant distribution, $f_a(0, s, y) \neq f_a(a_0, s, y)$. For instance, the increase in performance may be high when awarded with the first dollars, but then decreasing as amount increase, due to the stickiness in the response of the student, $f_a(0,s,y) > f_a(a_0,s,y)$ - e.g. students may react strongly increasing their hours spent in the library when they get some amount of grant, but the second derivative may be decreasing in the amount of grant since their capacity to adjust hours is sticky if already exerting a high level of effort.

When performance standards are considered in the framework, the cross-derivative (i.e. $f_{as}(0,\underline{s},y)$ should be investigated. 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 derivative depend also on the amount of grant where is evaluated. Following the above criterion, $f_{as}(0,s,y) > 0$ (i.e., an increase in grant amount will have larger effect on performance when incentives are stronger). However, it may be the case that when evaluated at high enough a_0, $f_{as}(a_0,s,y)$ is close to zero (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 $f_{as}(a_0,s,y) > 0$ (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).

6 Results

6.1 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. The forcing variable is the relative distance to the household after–tax income cutoff. This type of endogenous sorting is more likely to occur in the common case where the treatment assignment rule is public knowledge Imbens and Lemieux (2008), as in this paper. As precise thresholds are public information and have not changed since 2010, a concern of manipulation at the cutoff arises especially 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 eligible for a positive amount of aid. Montalvo (2018) highlight the fact that after–tax income is more difficult to manipulate than income, and in Spain the changes in the tax code are frequent.

Figure 3 shows the graphical representation of the density estimates in the vicinity of the cutoffs, displaying that it does not seem to be systematic manipulation of household parental income around the thresholds. The density of applicants increased as parental income decreased in T1 grant, given the fact that more students may be encouraged to apply as they were closer to the cutoff. Density estimates at T2 grant were roughly constant, since applicants have incentives to apply on both sides as they would be awarded with s positive cash allowance. The test statistics proposed by McCrary (2008) fail to reject a statistically significant jump at the eligibility cutoffs for any of the treatment samples used in this paper (i.e. period, gender, predetermined ability, etc.).[30]

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 "high" 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 (i.e. gender, nationality, parental income, PAU score, parents' occupation, etc.) as dependent variable. Panel A of Table 3 presents the regression results, showing that the observable characteristics of applicants are well balanced, since less than 10 percent of the variables do change discontinuously at income eligibility thresholds. Furthermore, 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, is 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 is variation in income, since the fraction of applicants who reported the same parental income than the one registered the year before is only 3.2 percent. Students' who were awarded a grant in a given year might be more likely to re–apply the next year. It might be 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 the density of re-application.[31]

[30] See online appendix (section B) for details of McCrary test's estimates for all treatment samples.
[31] See online appendix, section B.

6.2 Discontinuities in Grant Amounts

In this subsection, I examine the discontinuities in average grant amounts awarded of 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 a T1 or T2 grant plotted against the relative income-distance to the relevant eligibility thresholds. The figure indicates that approximately 98 percent of the theoretical eligible applicants received the grant.

Figure 5 presents the average conditional grant amount for all treatment samples as a function of applicants' relative distance to the thresholds separately for the two periods under study. The results indicate a clear discontinuity in the average conditional cash allowance for T1 and T2 grants in both periods, which is confirmed by the statistically significant results showed in Table 4 (Panel A). T1 grant provides not statistically significantly different average grant amount for both periods, with an average cash amount of 675 euros in Period I and 825 euros in Period II (relatively to been awarded with fee waiver). T2 grant reports a drastic decrease in the average grant amounts awarded across periods, with an average increment in the cash amount of 2,955 euros in Period I and 1,240 euros in Period II (relatively to T1 grant cash awards), and both estimates are statistically significantly different.

6.3 Impact on Dropout

Most of the literature focuses on the extensive margin effect of grants on enrollment. When there is an effect on enrollment (which is often stronger for freshmen students), disentangling the intensive margin response on performance is challenging (due to the potential selection bias that the enrollment effect provides). An advantage of the setting under study is the specific timing of grant applications in Spain, which allows to estimate the effects of grants on students who are already enrolled, and for whom dropout rates are relatively small. Table 5 displays the RDD estimates on dropout from higher education. 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 suggesting that the effect of grant on student performance do not seem to be biased by dropout effects. This result is consistent with Montalvo (2018), finding no effect on dropout of a sharp increase in tuition fees in a highly comparable setting.

6.4 Impact on Student Performance

I focus on the average GPA, which in Spain can take values between 0 (the minimum grade) and 10 (the maximum)[32] and the fraction of credits that the student passed among the total attempted credits as measures of student performance.

Figure 6 plots the average GPA for all treatment samples as a function of applicants' relative income-distance to the thresholds separately for both periods studied. The solid black lines are the fitted values from a linear projection. The average GPA is slightly different across periods for the two samples of applicants (around the T1 and T2 grant thresholds respectively). The average GPA was around 5.9 points in Period I and 6.15 points in Period II. Table 4 presents the non-parametric RDD estimates.

Result #1: No effect of neither small nor large discontinuous change in grant amounts when interacted with *weak* academic standards. I find no effect of relatively large cash allowance (neither for 675 nor for 2,955 euros) on student performance in Period I, when performance requirements were comparable to the performance incentives that characterize the typical need-based grant programs around the world (*weak*). This result is significant, since 2,955 euros of increase in the amount of cash allowance is a large grant amount in comparison with the average amounts awarded in other related papers under similar frameworks. Students do not seem to be particularly sensitive to large changes in cash amounts when interacted with academic requirements that are *weak*.

Result #2: Positive effect of relatively small discontinuous change in grant amounts when interacted with *strong* academic standards. I find that being eligible for an average of 825 euros grant (relatively to being eligible for only fee waiver) interacted with *strong* academic requirements, increases student average GPA and fraction of credits earned by 0.45 points and 6 percentage points respectively, which corresponds to an increase of approximately 7.3 and 7.6 percent with respect to the baseline mean. The T1 grant threshold offers a unique opportunity to analyze the role of academic requirements in the total effect of financial aid on performance. Since average grant amounts are not statistically significantly different between Period I and Period II, I can test the effect of the same grant amount under two different intensities of academic requirements. The effect of a change in the grant amount is not statistically significant when

[32] 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+.

academic requirements are *weak*, but statistically significant when *strong*. I use a Difference-in-Difference-RDD to test whether the estimates are not statistically significantly different across periods. The null hypothesis that both effects are equal across periods is rejected at the 1 percent confidence level. The results suggests that academic incentives augment the effectiveness of aid in improving student performance for those students who are changing from zero to some positive cash amount.[33]

Result #3: Results seems to persist over two consecutive academic years. Being eligible for a grant may have dynamic effects over a student's academic career. Grants awarded in a given year may produce long-lasting effects, 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 certain level of household income), it is possible to compute the cumulative average GPA and fraction of credits earned over subsequent years. This method would provide potential unbiased estimates and less concern for sample selection, but potentially the first stage would decrease over time due to the variability of students' application status and household income.[34] Local linear regression estimates indicate that being eligible for a grant under *strong* performance-based incentives increases the cumulative average GPA and fraction of credits earned over two years by 0.5 points and 6.3 percentage points per year respectively, which corresponds to an increment of about 8 and 7 percent per year with respect to the baseline mean. The eligibility for a grant interacted with strong performance standards seems to have a positive impact on student performance that last for two consecutive years.

Result #4: Large discontinuous change in grant amounts when students are already awarded with non-zero financial aid has no differential effect, irrespective of the academic requirements. Students do not seem to react differentially to discontinuous changes in the amount of grant when they are already receiving certain amount of cash, neither when academic requirements are *weak* nor *strong*. The interpretation of the non-significant results at the T2 threshold is ambiguous. It may be due to the fact that academic requirements affect differently students who are entitled to different levels of grants (students behavioral response to incentives may be more powerful when they start receiving some amount of grant), though

[33] Results of the Difference-in-Difference RDD are displayed in the online appendix, section E.

[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.

the incapacity of students in the lowest part of the income distribution (T2 grant applicants) to react to incentives due to their potential lack of ability for developing effective study strategies, or the fact that positive effect of stronger academic requirements may be offset by the potential negative effect of large decrease in the cash allowance awarded between Period I and Period II.[35]

6.5 Robustness Checks

In this section, I perform a number of tests in order to check the robustness of the baseline estimates: (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; (v) check for an effect of being eligible for only fee waiver; (vi) investigate the effect of being eligible for T3 grant in Period I; (vii) analyze potential effects in 2012 where academic requirements were slightly modified. 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*. The differences between the robustness checks and the baseline estimates are not statistically different. In addition, the null effect of the grant under the other different thresholds (T2 and fee waiver grant) and periods is also robust and persistent for each sensitivity check performed.[36]

Sensitivity to the Choice of Bandwidth. I analyze the sensitivity of the non-parametric estimates to the choice of the bandwidth changing the bandwidth size to half and twice the value of the optimal bandwidth proposed by Imbens and Kalyanaraman (2012). Results are very similar to those obtained in the baseline estimates, but larger when using half the optimal bandwidth than double.

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

[35]The interpretation of the results is discussed extensively in the Discussion section of the paper.
[36]See online appendix (section D) to see the details of robustness checks.

for confidence intervals (robust bias-corrected), I test the effects using the optimal bandwidth proposed by Calonico, Cattaneo and Titiunik (2014). The point estimates are very similar to the baseline estimates and the difference is not statistically significantly different.

Individual Control Variables and Year Fixed Effects. I investigate the volatility of baseline results when adding individual predetermined students' characteristics (e.g. PAU percentile rank, gender, or being enrolled in a STEM degree) and year fixed effects that capture time trends in the outcome variable. Results are statistically significant at the 5 percent confidence level with the point estimate smaller than baseline estimates, thought the difference is not statistically significantly different.

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. Points estimates are close to zero and non-significant in all specifications.

Fee Waiver Grant (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 an amount of cash. This eligibility threshold (T0) is very close to the eligibility cutoff of T1 grant. Hence, it is difficult to construct two treatment samples between T1 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 grants types where students were awarded with certain cash amounts (in T1 and T2 grant). I conduct a separate analysis of the treatment effect of being eligible for only tuition fee. Results shows no evidence of statistically significant effects on awarded cash amounts and student performance at this income-eligibility threshold.

Displacement and Other Needs Grant (T3): The importance of performance standards intensity. Figure 5 and Figure 6 display the fact that with equal average cash amount granted, an allowance setting with strong performance-based components seems to be more effective to enhance student performance, as opposed to a setting with weak incentives. An additional robustness check is testing whether there is some statistically significant effect at T3 threshold (working only in Period I) where the amount of cash awarded was similar to the one awarded for non-movers in Period II. When academic requirements are weak, there is no statistically significant effect of being eligible for a grant in every income-eligibility thresholds (T3, T2 and T1), which reinforce the baseline results of zero effect in the absence of strong requirements.[37]

Differential effects on 2012. This section test for specific effects of the grant in 2012. While academic incentives in Period II were homogeneous throughout the three academic years, Period II reported a change in 2012. In 2012 the requirements rose to 65 (90) percent for students enrolled in STEM (non-STEM) degrees. The null hypothesis of zero effect of the grant on student performance and dropout cannot be rejected. The results suggest that a single increase in the fraction of credits earned is not enough to affect student performance. This points toward the apparent important role that design rather than the existence of certain academic incentives have on stimulating student performance.

6.6 Heterogeneous Effects of Grants on Student Performance

Despite of the robust baseline estimates, investigating the existence of heterogeneous results for academic term (Fall vs. Spring grades) and different subgroups of population (gender, pre-determined academic ability and residence status) is necessary to understand the implications of the estimated effects.

Student Performance by Academic Term. 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, conceded grants were divulged between February-March on average. 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. An ideal way to test whether there is heterogeneous effects of the grant on student performance before or after the student received the notification, it 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, leading to a significant break in the density at income thresholds.[38]

[37] For further analysis of this robustness check see online appendix, section D.

[38] Notice that student disclosure time is not a perfect continuous variable, but rather discrete, since groups of students were receiving notification at the same time as they were sent in blocks.

An alternative way to test it is to look at the impact of the 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 6 presents the non-parametric estimates by academic term, confirming this hypothesis. The effect sizes are larger for the second than first term. Although the difference is not statistically significant, the estimates for Fall Term seem to be more sensitive to the functional form, as can be seen in Figure 7 and Figure 8.

Student Performance by Subgroups of Population. Table 7 and Table 8 presents the RDD estimates for T1 and T2 grants by period and subgroups of applicants. The positive effect of the T1 grant on student performance coupled with more stringent performance incentives are found for both males and females, but the magnitudes differ (Panel A). The point estimate is statistically significant for males, but it is not statistically different of female's.

Panel B explores heterogeneous effects by level of academic ability, dividing the samples into two groups based on applicants' percentile rank on PAU exam. Being eligible for a T1 grant in a setting with high incentives has significantly positive effects on student performance for students above the median percentile rank of the PAU exam score distribution. 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 both applicants who were living with their parents in the Region of Madrid (non-movers hereafter) when they enter university and students who were living away from their family home (movers hereafter). The null hypothesis of equality of coefficients cannot be rejected. While students living away from their family home receive positive amounts decreasing in the second period (from 2,858 to 1,673 euros on average), applicants who live with their parents earned a zero amount in the first period and 445 euros on average in the second period.[39]

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 445 euros, interacted with strong academic incentive components leads to a positive impact on students' average GPA of 0.45 points (7 percent with respect to the baseline mean). In addition, despite of the reduction on the

[39] See online appendix, section C.

amount of grant awarded for movers across periods, being eligible for an average grant of 1,673 euros (relatively to being eligible for fee waiver) under strong academic requirements, increases students' average GPA by 0.52 points (8 percent with respect to the baseline mean). The null hypothesis that both effects are equal across movers and non–movers cannot be rejected.

6.7 Mechanisms

This section investigates whether the performance increments observed are due to an actual rise in student success and not to other confounding factors (e.g. students taking easier subjects). Table 9 presents the results of the RDD estimates on different outcomes for T1 and T2 by period, and Figure 9 plots these different channels, reinforcing the results than the non-parametric estimates.

Final exam attendance rate. Panel A shows that being eligible for an average cash allowance of 825 euros (relative to fee waiver only) increases 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 (93 percent), qualifying for such level of grant enhances this average by 3.2 percentage points, which corresponds to an increase of about 3 percent with respect to the baseline mean.

Fraction of Subjects in Retake. Eligible students may increase their attendance rate to final exams through attending more often to retakes. Panel B present that being eligible for an average cash allowance of 825 euros (relative to fee waiver only) decreases the fraction of subjects that students have to retake by 4.6 percentage points, which corresponds to an increase of about 25 percent with respect to the baseline mean when interacted with *strong* academic requirements. Students seem to be increasing their fraction of credits earned in final exams directly, and not through an increase in the fraction of retakes.

GPA on final exams taken. Students who received the BCG grant may attend to final exams with higher frequency, while their performance on them may remain unchanged. The fact that students show-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, rather than to an 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 took. Results in Panel C shows that students who were eligible for an average cash allowance of 825 euros (relative to fee waiver only) under a setting with strong performance-based incentives improved their average GPA in final exams taken by 0.35 points, which corresponds to an increase of about 5 percent with respect to the baseline mean. The null hypothesis of zero effect is rejected at the 1 percent confidence level, indicating that the observed improvement in average student performance is genuine.[40]

Total Credits Enrolled. Students may be more conscious on the number of credits in which they enroll. Panel D present that being eligible for an average cash allowance of 825 euros (relative to fee waiver only) increases the total credits enrolled in a given academic year by 3.5 credits, which corresponds to a decrease of about 5 percent with respect to the baseline mean when interacted with *strong* academic requirements. The magnitude of a decrease in 3.5 credits is about half of an average subject.

GPA on mandatory and elective subjects. 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 specific to every degree, and several mandatory courses which are compulsory and degree specific. If applicants were to self-select in easier subjects, it is reasonable to expect that it would for elective courses, due to the fact that such courses are those for which students con select different subjects. Panel E and F analyze the effects of the grant on the average GPA for mandatory and elective courses. Applicants who were eligible for an average cash allowance of 825 euros (relative to fee waiver only) under strong performance-based incentives, increases their average GPA on those subjects which are mandatory by 0.46 points, which corresponds to an increase of 7.5 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.[41]

[40]However, this result seems to be slightly sensitive to the functional form used.

[41]Investigating the point estimate and the standard errors, it seems plausible that there is no statistically significant effect on the average GPA of elective courses due to sample size limitations in order to identify a smaller minimum detectable effect.

6.8 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 825 euros (relatively to the tuition waiver) in the period when performance requirements were more stringent, increases student's chances of obtaining a degree in 12.5 and 11 percent with respect to the baseline mean for all applicants and if the applicant is on the graduation year respectively. In contrast, the null hypothesis of zero effect on degree completion under a setting with *weak* academic requirements cannot be rejected.

7 Discussion

The Spanish national need-based grant program provides a unique design to analyze the causal effect of this form of financial aid on student performance and graduation. I find no effect of relatively high cash amounts on student performance (average GPA and fraction of credits earned) and degree completion in a setting with *weak* performance incentives comparable to the typical need-based grant programs around the world. These results are consistent with papers finding no effect of similar Pell Grant's cash amount on student GPA interacted with relatively similar academic requirements (Denning, Marx and Turner, 2017; Denning, 2018). In contrast, I find that an average provision of 825 euros cash allowance (relatively to receiving only fee waiver) increased student performance and probability of degree completion in a setting with more demanding performance-based incentives, but zero effect at a higher level of grant. The size of the effects is similar to Scott-Clayton (2011), the most related paper. Effects are larger than Angrist, Oreopoulos and Williams (2014), and slightly lower than those found only for women in Angrist, Lang and Oreopoulos (2009). Students enhance their final exam attendance rate and their GPA on final exams taken. Eligible students reduce the fraction of subjects that have to retake and the total amount of credits in which they enroll. I ruled out the hypothesis that results are driven by student selection of less demanding courses or dropout from higher education.

7.1 External Validity

A potential important concern of this paper is the fact that results might be difficult to generalize to other settings. 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 collegians 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 their counterparts in the rest of Universities 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.[42] 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.[43]

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 entitled to both fee waiver and need-based grants.

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

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

7.2 Interpretation of Results: Efficiency and Equity

Efficiency. This paper points out the importance of minimum academic requirements on need-based grants' cost-effectiveness. From the efficiency point of view, a program with strong performance standards presented a differential performance improvement for those students whose comparison group was receiving only fee waiver and zero cash amount. In contrast, the grant did not seem to affect differentially those students whose comparison group was awarded with a certain cash amount, neither under a setting with *weak* nor *strong* academic standards. Three hypothesis may help to interpret the results.

First, the null impact of the grant could alternatively be due to the fact that students at the bottom of the family income distribution may not be as able as their peers to respond to performance incentives, even under 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 U.S. 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).

Second, students behavioral response to incentives may be more powerful when they start receiving some amount of grant. Effects seem to be large with small amounts of grant when changing from zero to certain positive amounts, but no differential effect is found when students are entitled to additional amounts. This result is consistent with Fack and Grenet (2015), a study in which the largest effects of the French national need-based grant program were concentrated on those students receiving the first endowment of cash allowance and not in 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). Incentives seem to work when there is some entitlement to the grant,but their effect is not clear with additional grant amounts. Interestingly, additional large changes in grant amounts when students are already awarded with non-zero financial aid, have no differential effect neither when interacted with *weak* nor *strong* academic requirements. Specially relevant is the case of the period with *weak* academic requirements, in which students increase their cash amount in 3,000 euros from 1,400 euros approximately, a large differential amount in relative terms to what is found in the literature of financial aid. Thus, student performance does not seem to be particularly sensitive to monetary incentives, and this result may potentially rule out the cost-of-college channel, though I cannot test this hypothesis directly in this paper.[44]

Third, the natural experiment is not exactly the same for those students at the bottom of the parental income distribution, since both cash amounts and academic standards changed across periods. Then, it is not possible to investigate whether those students would react differently under the same amount of grant interacted with *weak* and *strong* academic requirements. I cannot reject the hypothesis that the large decrease in average amounts across periods may offset the positive effect induced by stronger academic standards.

Equity. The equity implications of increasing academic requirements on grants devoted to low-income students may be ambiguous. The intuitions of the Bénabou and Tirole (2000) model, increasing standards may encourage additional students to exert higher effort, but other lower ability students may give-up and dropout from higher education. An extension of this model including financial aid (Scott-Clayton and Schudde, 2016) show that discouragement (dropout) would be concentrated among those in the lower part of the ability distribution, while encouragement (improved GPA) may be concentrated among those who are close to the performance requirement threshold. The significance and magnitude of these effects may be student (e.g., distribution of parental financial constraints, student ability, etc.) and country specific institutional dependent (e.g., cost of college).

First of all, it is important to elucidate whether the increase in academic requirements was binding. Unfortunately, I cannot directly measure the actual stringency of the policy, given that it is unlikely that students apply for a grant if they know that do not meet the academic requirements. It would be reasonable to expect that the annual fraction of applicants who are not eligible for performing below the academic requirements grows when those increase, but this number was about 26 percent and was fairly constant over the period.[45] However, an approximation may be undertaken in order to proxy the tightness of academic requirements. For income-eligible applicants who apply for a grant in 2010 and 2011, I measure that 23 and between 35–43 percent would not meet the academic requirements if they were *weak* and *strong* respectively. For first year students, I compute that 30 and 47–55 percent would not be eligible to renew the grant in those two scenarios. Although the previous estimates contains measurement error, they seem to indicate that the policy was binding.[46]

[44] This channel implies that the relaxation of budget constraints may prevent financially constrained students from working part-time, inducing them to devote more time to study.

[45] Note that this is not a problem of internal validity, but to address how binding the policy was.

[46] Schudde and Scott-Clayton (2016) calculate that between 25-40 percent of first year Pell recipients at public

To determine the net size of this increase, the positive effects in performance induced by the grant with *strong* academic requirements should be taken into account, which potentially make some students to meet the new threshold (inducing them to be *more ambitious*). I compute that 8 (11) percent of all (first year) students would have meet the requirements as a consequence of being affected by the average effect of the grant with *strong* standards on fraction of credits earned and average GPA, under the assumption that the average effect would be constant on the distribution of income-eligible students. This measure raises to 11 (14) percent of all (first year) students, when looking at the counterfactual of those students who start receiving some cash amount (students who were eligible to only fee waiver and not cash amounts). Then the increase in the fraction of potentially eligible students who would not keep the grant does not seem to be drastic, since the positive effect of the grant with *strong* requirements counteract the negative impact of the raise in requirements by making some students *more ambitious*.

In order to analyze whether the increase in the academic requirements have statistically significant effects on student dropout from higher education (whether induced some students to *give up*), a more thoughtful investigation is required. I perform a RDD to observe differential changes in dropout at the income-eligibility cutoffs, a Difference-in-Difference model (DID) and a Logit analysis to measure the propensity to dropout before and after the change in requirements. I do not find significant equity effects of an increase in the academic requirements. At the vicinity of income-eligibility cutoffs, there is no evidence of a differential 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. These results show the local average treatment effects estimated with the RDD, but do not provide average effects for the total distribution of grant applicants. To address whether students would dropout as a consequence of not meeting the *strong* academic requirements, I perform a DID analysis comparing students who performed higher to the *weak* academic requirements but not overcame the *strong* (Treatment Group), with students who do not meet the *weak* academic requirements (Control Group), before and after the reform. I find no statistically significant effect of the reform on drop out from higher education, showing that the group of students who would not meet the requirements due to their increase do not significantly give up and dropout. An additional Logit analysis on the full population of grant applicants over 2010–2015 shows that the probability of dropout from higher education does not statistically significantly change

institutions were placed at risk of loosing financial aid.

after the increase of requirements. These results seem to be robust for first and non-first year students. In addition, the ability of students who apply for a grant (measured as the percentile rank in the access to university exam) does not change significantly after the reform. Stronger performance standards do not seem to have a significant equity effect on applicants to need-based financial aid.[47]

To interpret the results across periods, it is important to address the issue of the comparability of applicants across periods. Note that this is not an internal validity concern, but an exercise to understand how similar the populations of grant applicants are across periods. As performance requirements are different by period, the type of students who apply for a need-based grant might significantly differ, comparing potentially different student types across periods. In an attempt to test the comparability of the two periods for each of the allowances studied, I display a t–test of the difference in baseline means of students' observable characteristics (such as gender, PAU test score, household income, parental occupation, etc.) by period and treatment sample. The null hypothesis of equality of the observable characteristics across periods cannot be rejected for 80 and 60 percent of the variables in the extensive margin of grant eligibility and in additional amounts cutoffs respectively.[48] Applicants seem to be highly comparable across periods for those students applying at the vicinity of the grant extensive margin, which sub-population of applicants present slightly higher family income and fraction of movers, but lower students with blue collar parents, in comparison with those of the period with *weak* academic requirements. However, there is a more different student composition for those students entitled to additional amounts (at the lowest of the household income distribution), which makes the comparison across periods more challenging.

The equity results seem to contradict the evidence that performance incentives have negative impacts on student persistence presented by Scott-Clayton and Schudde (2016) in the US and Lindo, Sanders and Oreopoulos (2010) in Canada. However, results are consistent with Montalvo (2018), showing no adverse impact of a tuition increase on low-income students enrolled at universities in the region of Catalonia (Spain). The institutional context, especially the cost of college, may potentially be a relevant factor affecting the elasticity of dropout with respect to academic requirements. A setting with stronger academic requirements appears to be cost-effective, at least partially.

[47] To see the Logit and DID analysis see Appendix, Section G.
[48] See online appendix, section F.

7.3 Potential confounding factors

Labeling Effect. Empirical evidence has shown that labeling may reinforce or mitigate the impact of an intervention. In the context of grants, Barrera-Osorio and Filmer (2016) show that providing scholarship labeled as need-based or merit-based matter for its effects on student performance, since both types of grants increased enrollment and attendance to school, but only the merit-based displays positive impacts on student achievement. After nine years in the program, Barrera-Osorio, De Barros and Filmer (2018) find that these differences remain, and those students on the merit-based program registered higher health and employment rates. In this paper, it is unlikely that the labeling effect may be a confounding factor of the results, since targeted population and label of the program remain constant over the period of study.

Other institutional changes. In an attempt to rationalize public expenditure, the Spanish government passed Law 14/2012, which raised college tuition fees from 2012/2013 onwards.[49] The Law increased the cost per credit on the number of times registered in a particular module, such that the cost per credit that students bear raised exponentially with the number of re-registrations in a particular module.[50] Beneito, Bosca and Ferri (2018) find that the increase in tuition fees reduces the average number of times students' register for a single module before passing it, increase the probability of passing with the first registration and raise their academic grades. A potential concern might arise on whether this change in the credit price across time might be a confounding factor of the impact of the grant. There are three reasons that potentially reject this idea. First, there are no statistically significant results of testing the isolated effect of being eligible for only fee waiver on student performance in none of the periods.[51] Second, the significant effects on T1 eligibility threshold are mainly comparing students who got fee waiver vs. those who were granted with fee waiver plus some amount of cash allowance, holding constant the tuition fees paid by the students on both sides of the cutoffs within each period. This is due to the fact that students closer to the eligibility threshold are weighted higher using a triangular kernel. Third, this paper focuses on applicants for a need-based grant, a population of students that is potentially different to the standard student enrolled at university, which is the focus of the study previously mentioned.

[49] *Real Decreto-ley 14/2012, de 20 de abril, de medidas urgentes de racionalización del gasto público en el ámbito educativo.*

[50] Law 14/2012 established that university tuition fees should cover between 15–25%, 30–40%, 65–75%, and 90–100% of the total cost of education for the first, second, third and fourth-time and subsequent registrations respectively in a particular module.

[51] See online appendix, section D.

In addition, a loan system was functioning in Spain from 2007 to 2011 for postgraduate studies. The timing – in the midst of a recession – was unpropitious and many students defaulted on their loan payments (OECD, 2015). The fraction of Master students covered by loans in 2010/2011 was only 2 percent. This program is unlikely to affect the results due to the tiny fraction of students covered, and by the fact that loans were offered for Master and PhD students, while this paper focuses on undergraduate students.

8 Conclusion

Using a regression discontinuity design in which I exploit the family income thresholds to being eligible for a grant, I estimate the causal effect of the Spanish large-scale need-based grant program on student performance (average GPA and fraction of credits earned) and degree completion. I find that an average provision of 825 euros cash allowance (relatively to receiving only fee waiver) increases student performance and probability of degree completion in a setting with demanding academic requirements. Students increase their final exams attendance rate and their GPA in final exams taken. Eligible students decrease the fraction of subjects that they have to retake and the total credits in which they enroll. There is no evidence of significant effects on student course selection or dropout from higher education. However, I find no effects of non-statistically different cash amounts interacted with academic requirements relatively comparable to those of the typical need-based grant programs around the world, such as the SAP of Pell Grants in the U.S.

This paper points out the significant role that minimum academic requirements to retain the grant play on stimulating student performance and degree completion in the national large-scale need-based grant programs. Student performance seems to be weakly correlated with monetary incentives, but more reactive to academic incentives. It seems that grants attached to *weak* academic requirements do not affect student performance, while grants with *stronger* requirements provide large and positive effects. The intensity and design rather than the solely existence of academic requirements matter for stimulating student performance. The mechanisms indicate that a setting with *strong* academic requirements may reduce costs for taxpayers on repeated subjects failures and long attainment time rates, and improve the benefit of eligible students by improving their performance. Academic requirements in the context of higher education financial aid seem to be an effective tool to overcome moral hazard problems, though the optimal intensity of those requirements may be institutional context-specific.

Although results may suggest that the effect on student performance is not linear to size of academic requirements, I cannot reject the possibility that the impact is in fact linear. It is still unclear which would be the distribution of the effects of a grant on performance and dropout along the different possible academic requirements (from zero strings attached to full accountability). Understanding how the impact of a grant changes when attached to all different possible academic requirements turns out to be a crucial research question, in order to improve the effectiveness of large-scale financial aid programs that cover a large fraction of students in higher education, and which spend sizable amounts of the public budget. Establishing the optimal line of academic standards and amount of financial aid that is socially optimal remains a topic for future research.

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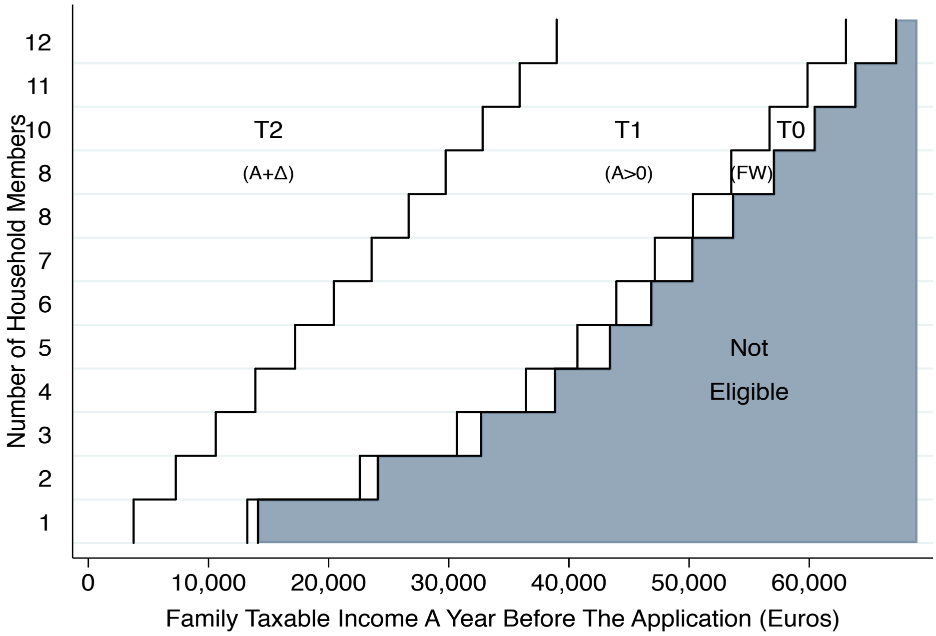
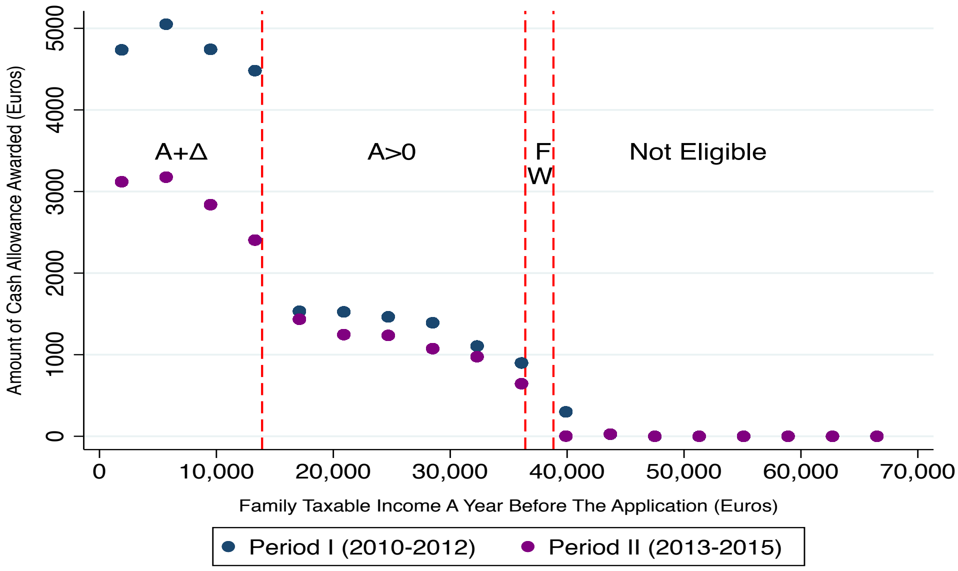
Figure 1: Income eligibility thresholds for the different levels of the BCG grant.



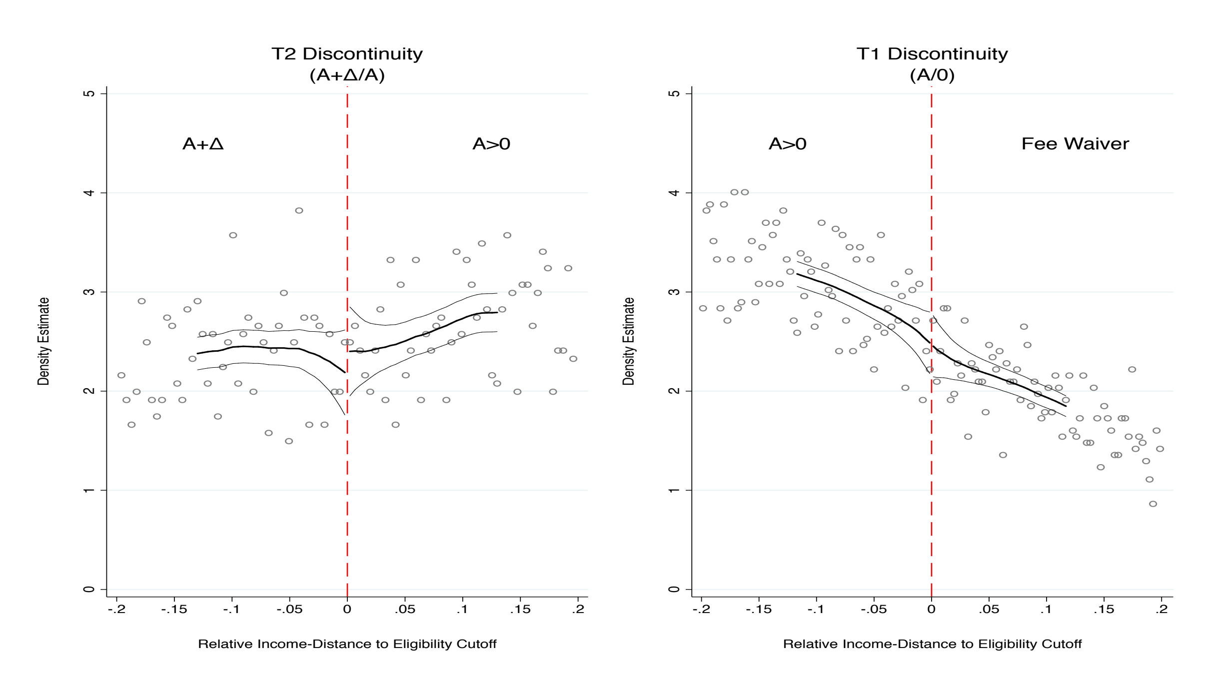
Notes: The figure depicts family income thresholds for different number of household members in the period 2010–2015. Thresholds are exactly the same amounts over the six-year period. T0 refers to T0 Discontinuity in which students receive the fee waiver grant (FW), T1 to T1 Discontinuity in which students are awarded with fee waiver and cash amount (A), and T2 to T2 Discontinuity in which students are awarded with fee waiver and larger cash amount $(A + \Delta)$ than (A). 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



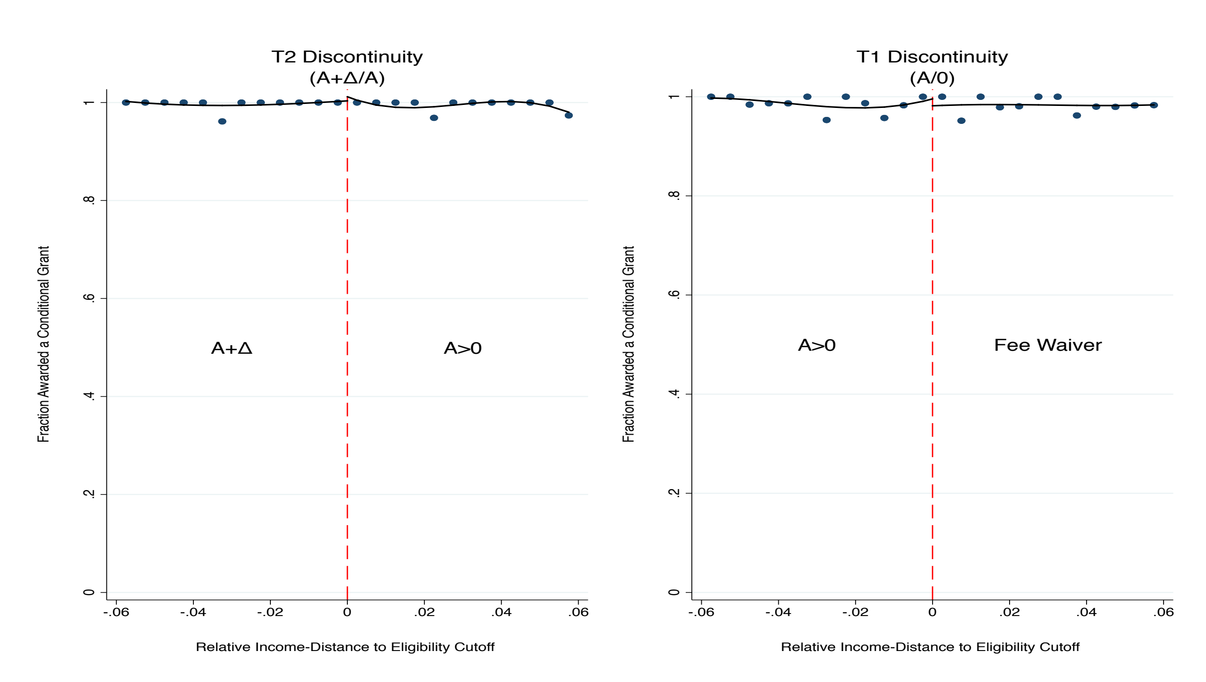
Notes: The figure depicts the amount of annual cash allowance awarded to applicants with 4 family members, as a function of their parents' taxable income by period. FW refers to students receiving the fee waiver grant, A to students awarded with fee waiver and cash amount (A), and $(A + \Delta$ to students awarded with fee waiver and larger cash amount $(A + \Delta)$ than (A).

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



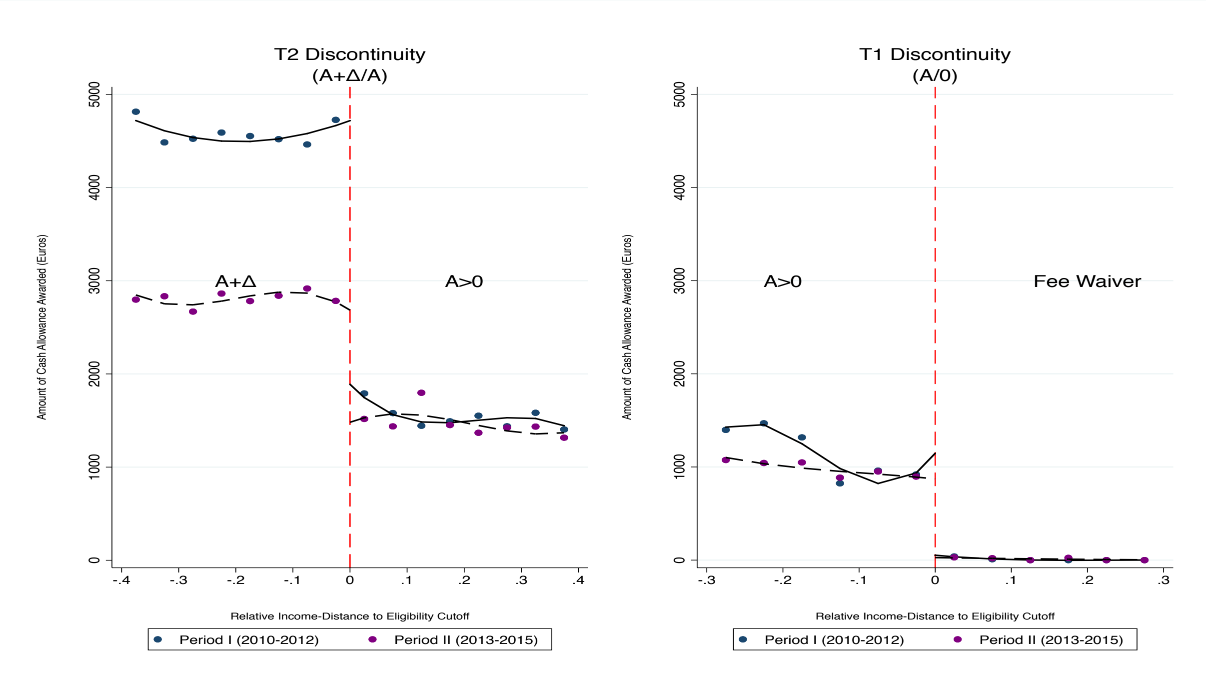
Notes: The figure shows the results of the test proposed by McCrary (2008). The weighted kernel density estimates are plotted, computed separately for each of the sides of the income thresholds T1 and T2. The T1 treatment sample includes applicants whose household parental taxable income is within 50 percent of the eligibility thresholds between fee waiver and Residence Grant allowances. The T2 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 T1 and T2 Discontinuities (2010–2015).



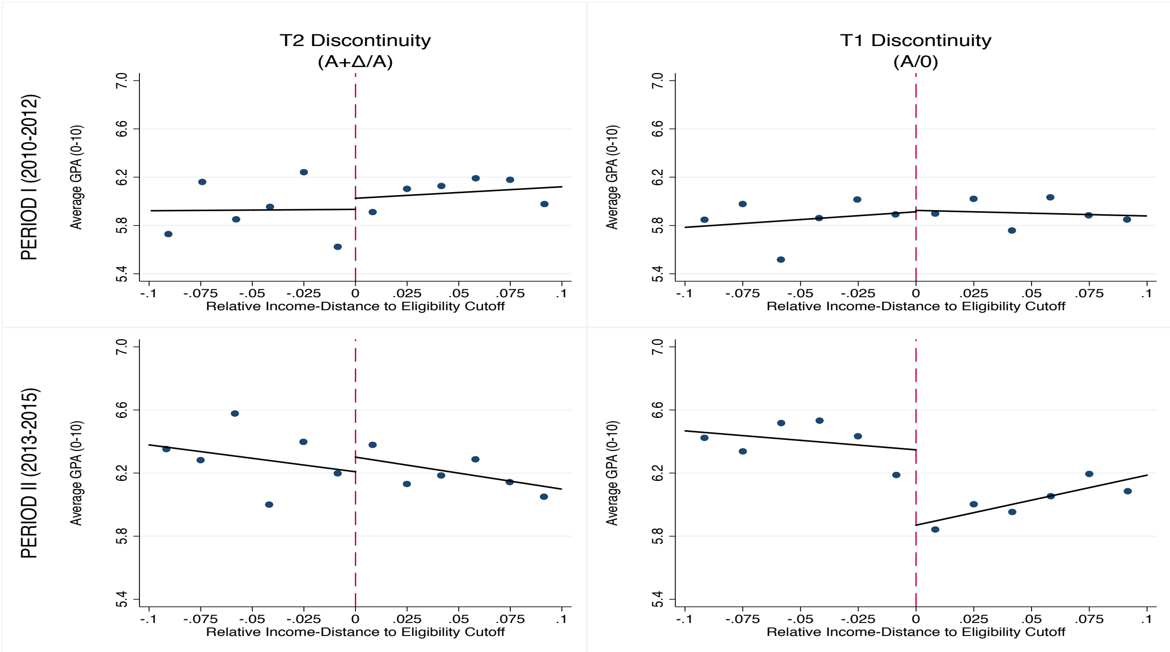
Notes: The dots represent the average fraction of applicants who were awarded a conditional grant per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "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 T1 and T2 Discontinuities by Period.



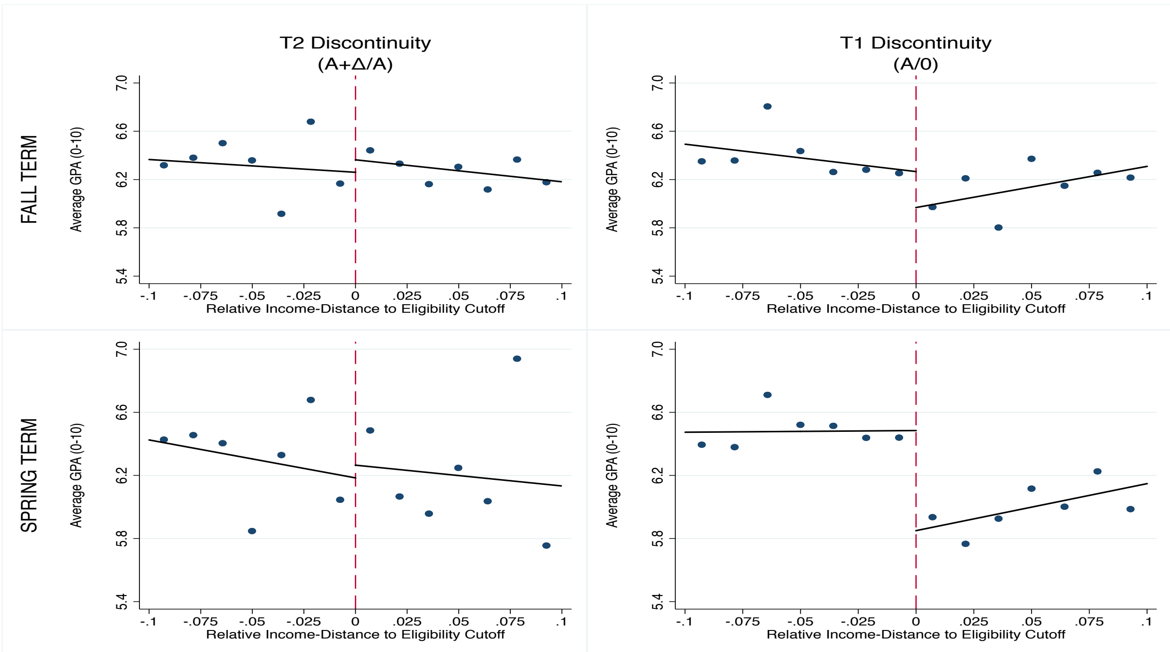
Notes: The dots represent the average grant amount per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility 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 T1 and T2 Discontinuities by Period.



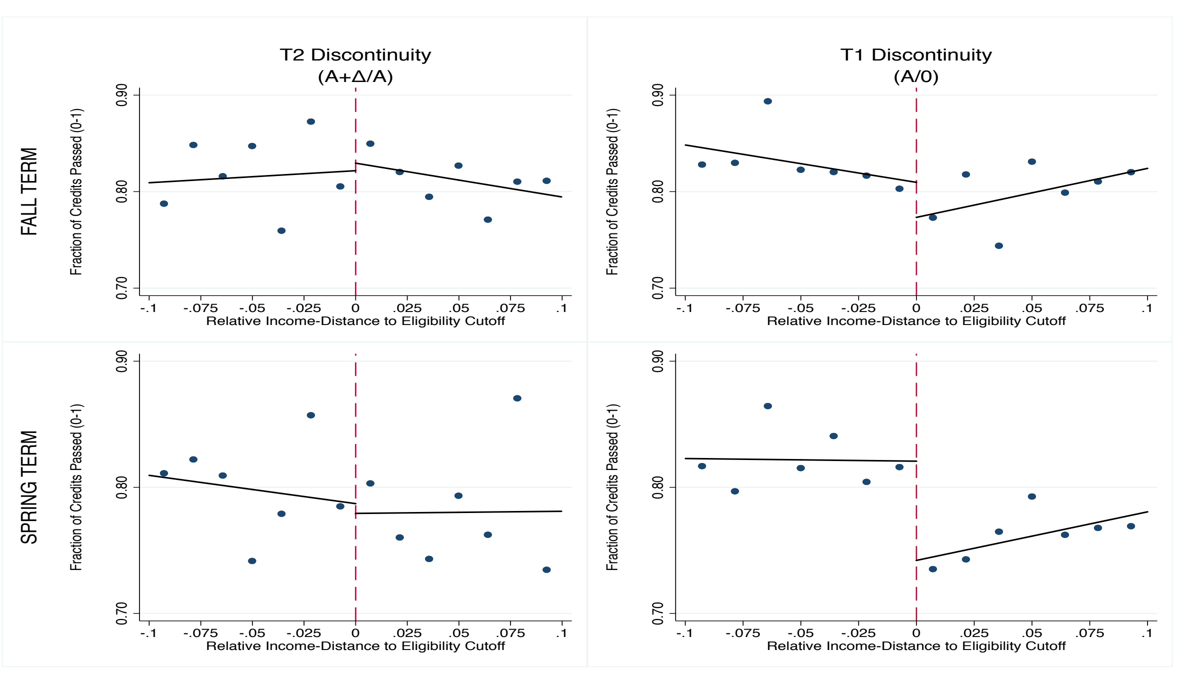
Notes: The dots represent the average GPAs per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility Cutoff" 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 T1 and T2 Discontinuities in Period II by Term



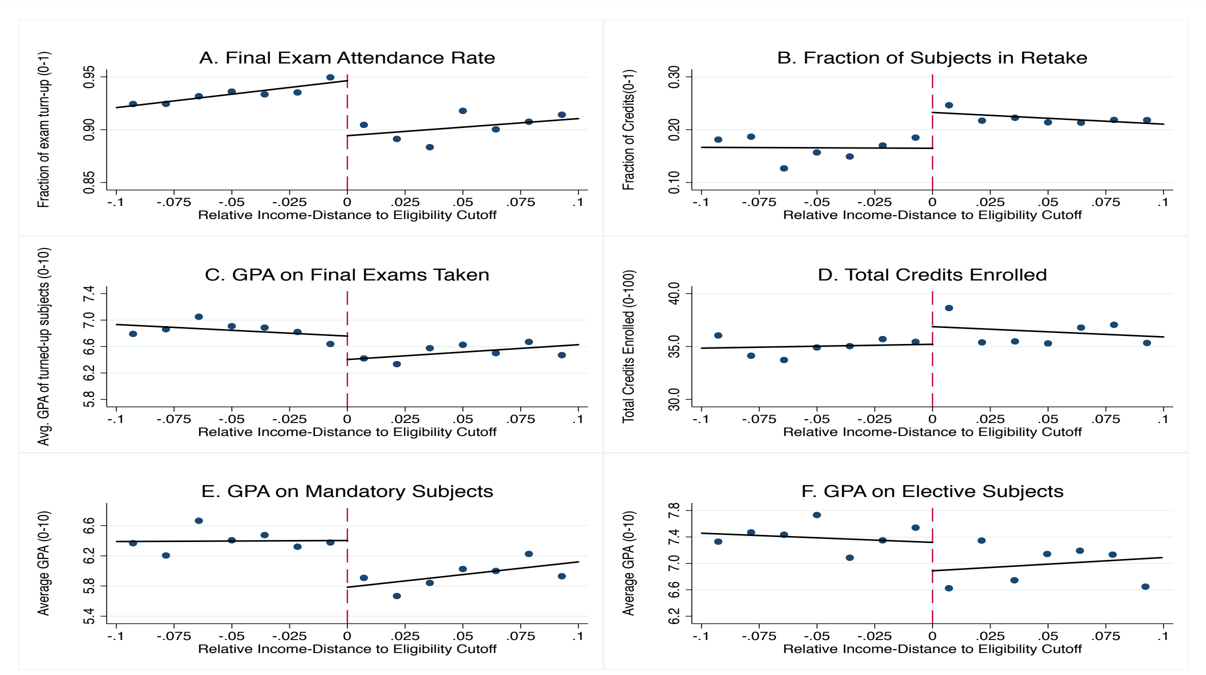
Notes: The dots represent the Average GPAs per interval of relative income-distance to the eligibility thresholds. The solid lines are fitted values from a third-order polynomial approximation which is estimated separately on both sides of the cutoffs. "Relative Income-Distance to Eligibility Cutoff" 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 Earned (0-1) for T1 and T2 Discontinuities over Period I and II by Term



Notes: The dots represent the fraction of credits earned 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 T1 Discontinuity (2013–2015)



Notes: The dots represent the average of the outcome variable 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)	**T2 Discontinuity** ($A + \Delta$/A) (1)	**T1 Discontinuity** (A/0) (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)
Undergraduate year		
First year	0.30	0.31
Second year	0.22	0.20
Third year	0.20	0.19
Fourth year	0.17	0.17
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 T1 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 T2 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)	**T2 Discontinuity** ($A+\Delta$/A)		**T1 Discontinuity** (A/0)	
	Baseline mean (1)	Non-parametric Estimates (2)	Baseline mean (3)	Non-parametric Estimates (4)
A. Each baseline charcteristic separatelly				
Female	0.48	0.015 (0.031)	0.46	0.033 (0.026)
Spanish	0.94	-0.014 (0.016)	0.99	0.003 (0.006)
Access to University Percentile rank	53.41	-2.044 (1.858)	56.36	3.46** (1.594)
STEM degree	0.35	0.004 (0.031)	0.41	-0.031 (0.025)
Households taxable income (euros)	17,282	-1.882 (233.841)	42,126	123.971 (308.907)
Disability	0.015	0.005 (0.009)	0.012	0.003 (0.006)
Large family condition	0.13	-0.000 (0.024)	0.13	0.007 (0.020)
#Family members	3.664	-0.004 (0.068)	3.651	-0.015 (0.047)
Live outside the family home	0.3	0.006 (0.028)	0.3	0.023 (0.023)
Entrepreneur Parent	0.073	0.007 (0.017)	0.04	-0.008 (0.009)
Blue Collar Parent	0.45	0.019 (0.032)	0.22	-0.041** (0.020)
Self-Employed Parent	0.061	0.026 (0.017)	0.021	-0.003 (0.008)
# Awarded Grants	0.061	-0.107 (0.097)	0.37	-0.020 (0.061)
First year	0.295	0.042 (0.031)	0.338	-0.012 (0.018)
Second year	0.225	-0.056* (0.029)	0.238	0.012 (0.017)
Third year	0.204	0.030 (0.023)	0.182	0.016 (0.016)
Fourth year	0.173	-0.019 (0.021)	0.148	0.005 (0.014)
B. All baseline charcteristic jointly				
X2-stat		14.37		22.99
P-value		0.57		0.11

Notes: The table shows the RDD non-parametric estimates for the different applicants' observable variables. The treatment effect is estimated using a triangular 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 T1 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 T2 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 Earned at Different Income Eligibility Thresholds and Periods.

Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** ($A+\Delta$/A)		**T1 Discontinuity** (A/0)	
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 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)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	5.97	6.29	5.91	6.15
C. Fraction of Credits Earned (0-1)				
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
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]	[1,860]	[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 earned (Panel C) and average accumulated GPA over two years (Panel D). The treatment effect is estimated using a triangular 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 T1 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 T2 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 Official Dropout from higher education at T1 and T2 grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** ($A + \Delta$/A)		**T1 Discontinuity** (A/0)	
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	0.017	0.020	-0.014
	(0.010)	(0.014)	(0.015)	(0.014)
	[3,402]	[3,549]	[6,095]	[5,87]
Baseline mean	0.02	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 triangular 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 T1 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 T2 treatment sample (column 2) includes applicants whose household parental taxable income is within 60 percent of the eligibility thresholds between Residence Grant and Compensate Grant allowances. Robust standard errors are clustered at the student level and displayed in parenthesis. The number of observations used in the non-parametric estimations are reported below the standard errors. Total number of observations are in squared brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Discontinuities in Average GPA and Fraction of Credits Earned at Different Income Eligibility Thresholds and Periods by Term.

Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** ($A + \Delta$/A)		**T1 Discontinuity** (A/0)	
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 Earned (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 GPA (Panel A) and fraction of credits earned (Panel B). The treatment effect is estimated using a triangular 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 T1 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 T2 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 7: Discontinuities in Average GPA (0-10) at T1 and T2 grants by period and subgroup of applicants.

Treatment Sample: (Income Eligibility Thresholds)		**T2 Discontinuity** $(A + \Delta/A)$		**T1 Discontinuity** (A/0)	
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 triangular 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 T1 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 T2 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. 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 Earned (0-1) at T1 and T2 grants by period and subgroup of applicants.

Treatment Sample: (Income Eligibility Thresholds) **Period:** (academic years)		**T2 Discontinuity** ($A + \Delta$/A) **Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**T1 Discontinuity** (A/0) **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 triangular 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 T1 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 T2 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. 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 T1 and T2 grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** ($A+\Delta$/A)		**T1 Discontinuity** (A/0)	
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	0.006	0.006	0.032***
	(0.016)	(0.012)	(0.012)	(0.010)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	0.904	0.932	0.912	0.929
B. Fraction of Subjects in Retake				
Non-parametric Estimates	0.004	-0.002	-0.013	-0.046**
	(0.025)	(0.020)	(0.019)	(0.018)
	[3,402]	[3,549]	[6,093]	[5,867]
Baseline mean	0.192	0.169	0.204	0.189
C. GPA on final exams taken				
Non-parametric Estimates	-0.040	0.074	-0.049	0.351***
	(0.156)	(0.139)	(0.106)	(0.129)
	[3,392]	[3,541]	[6,077]	[5,859]
Baseline mean	6.512	6.699	6.396	6.552
D. Total Credits Enrolled				
Non-parametric Estimates	-0.503	0.429	1.275	-3.558**
	(2.432)	(1.636)	(1.891)	(1.595)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	78.41	71.34	78.34	73.78
E. GPA on Mandatory Subjects				
Non-parametric Estimates	-0.084	0.107	-0.050	0.462***
	(0.200)	(0.172)	(0.128)	(0.152)
	[3,397]	[3,548]	[6,089]	[5,865]
Baseline mean	5.908	6.210	5.868	6.103
F. GPA on Elective Subjects				
Non-parametric Estimates	-0.689**	-0.056	0.136	0.553
	(0.326)	(0.288)	(0.205)	(0.385)
	[1,298]	[1,288]	[2,134]	[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' outcome variables. The treatment effect is estimated using a triangular 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 above the eligibility threshold. The T1 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 T2 treatment sample 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 at T1 and T2 grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** $(A + \Delta/A)$		**T1 Discontinuity** (A/0)	
Period: (academic years)	**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (4)
A. Probability of Graduation				
Non-parametric Estimates	0.007	0.116	0.008	0.100*
	(0.020)	(0.073)	(0.023)	(0.056)
	[2,253]	[1,151]	[4,842]	[1,947]
Baseline mean	0.93	0.92	0.91	0.8
B. Probability of Graduation in Graduation Year				
Non-parametric Estimates	-0.008	0.000	-0.022	0.102*
	(0.022)	(0.000)	(0.021)	(0.056)
	[515]	[428]	[863]	[723]
Baseline mean	0.98	0.99	0.99	0.95

Notes: The table shows the RDD non-parametric estimates for the different applicants' degree completion. The treatment effect is estimated using a triangular 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 T1 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 T2 treatment sample 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:

"Countering moral hazard in higher education: The role of performance incentives in need-based grants"

(not intended for publication)

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October 2018

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), an RDD-DID reduced-form model (section E), the comparability between Period I and Period II (section F), the potential equity effects (section G), and the minimum academic requirements to being eligible for a BCG grant (section H).

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 (T3) 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 T1 Discontinuity. 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 T1 and T2 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 T1 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 T1 and T2 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 T1 grant on both periods, and similar estimates for T2 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 (T2 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 T1 grant. It makes difficult to construct two treatment samples between T1 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 T1 and T2 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 (T3, Threshold 3)

An additional robustness check is testing whether there is some statistically significant effect at T3 threshold (working only in Period I) where the amount of cash awarded was similar to the one awarded for non-movers in Period II. As a robustness check, I use the T3 grant for non-movers as comparison group for T1 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.

An ideal test would be a similar amount of cash awarded for non-movers at Period I and II for T1 grant, but unfortunately this is not the case. As a robustness check, I use the T3 grant for non–movers as comparison group for T1 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 T3 cutoff are twofold. First, the T3 grant was located 15 percent of the relative distance below the T1 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 T3 in Period I, which makes the comparable group similar to non-movers at T1 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 T3 grant as a comparison group for T1 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 key advantages of using the T3 cutoff are twofold. First, the T3 grant is located 15 percent of the relative distance below the T1 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 T3 in Period I, which makes the comparable group similar to non-movers at T1 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 T3 grant as a robustness check for T1 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 T3 in Period I was 543 euros for non-movers, and cash endowments at T1 in Period II was 410 euros for non–movers. However, the null hypothesis of zero effect of being eligible for the T3 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).[52]

Student performance was not impacted by T3 grant in Period I, and it was positively impacted in Period II by the T1, under approximately the same cash allowance amounts but different incentives. This finding 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 grant's effect on performance.

Table D2 presents that the average discontinuity in cash allowance at T3 in Period I is 543 euros for non-movers, and cash endowments at T1 in Period II is 410 euros for non-movers. However, the null hypothesis of zero effect of being eligible for the T3 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).[53]

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 earned) and dropout cannot be rejected.

The results suggest that a single increase in the fraction of credits earned does not affect student performance. This points toward the direction of this paper's conclusion concerning

[52] 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.

[53] Results available upon request.

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.

E RDD-DID

I perform a reduced-form analysis of RDD-Differences-in-Differences (RDD-DID). Let $E_{i,k,t}$ be a dummy variable that takes value one if applicant i is eligible for a grant of level k ($k = 1, 2$) at year t, and zero otherwise. Eligibility for a level k grant is a deterministic function of the applicant's net household taxable income c_{it} and the number of family members m_{it}:

$$E_{i,k,t} = \mathbb{1}\{c_{it} \leq \bar{c_k}(m_{it})\} \tag{19}$$

$$Y_{it} = \alpha + \sum_{k=1}^{2} \beta_k E_{i,k,t} + c_{it} + c_{it} * E_{i,k,t} + \epsilon_{it} \tag{20}$$

Let Period II be a dummy variable that takes value one if years 2013-2015 (Period II). The coefficient of interest is β:

$$Y_{it} = \alpha + c_{it} + c_{it} * E_{i,k,t} + + c_{it} * \text{Period II} + c_{it} * E_{i,k,t} * \text{Period II} + E_{i,k,t} + \text{Period II} + \sum_{k=1}^{2} \beta_k E_{i,k,t} * \text{Period II} + \epsilon_{it} \tag{21}$$

Note that in this model, the coefficient estimates do not change. It is the are the same that perform a RDD separately by each period than RDD-DID in terms of the coefficients (standard errors can slightly vary because of the degrees of freedom). The advantage of this model is the fact that this method allow us to compute the standard errors of the difference in changes directly, since it is not straightforward to compute the standard error of the difference between the two coefficients estimated separately by period (it would require bootstraping).

Results are reassuring on non-statistically different average grant amounts across periods, an increase in student performance and degree completion, and no statistically significant effect on dropout from higher education.

F 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 T1 and T2 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 T1 grant, and for more than half in T2 grant.

G Equity Effects

In order to analyze whether the increase of academic requirements have significant equity effects to the average population of applicants to the grant, I performed a Logit analysis and a Difference-in-Difference (DID) model, in addition to the RDD analysis presented in Table 5. I count as dropout from higher education if the student's file label as close (i.e., student has not graduated and file has not been moved to another higher education university). The analysis explores two different dropout variables: (i) Yearly dropout, signaling the flow of students who dropout at the end of certain academic year (open files are included in this computation); (ii) Net dropout, which is the total cohort dropout (in this variable, the student can only be graduated or dropout). This method uses two approaches: (i) Compares two cohorts, first (non-first) year students applicants the previous year of the reform versus the year of the reform; (ii) Uses the full span of six-year period to see how dropout changed before and after the reform.[54] The regressions control for all available student predetermined observable characteristics.

The Logit analysis shows that, in general, female and students with higher rank in the access to university exam presents lower probability of dropping out, but movers and non-first year enrolled in STEM degree show higher probability of drop out. However, both dropout measures do not significantly change after the reform, neither when controlling for student individual observable characteristics nor when do not . This results are robust for non-first year and first

[54]Note that for the first approach I can only use the first change in the reform at 2012/2013, since I have data from 2010–2015. Net dropout rate for cohort 2013/2014 would be bias, due to the fact that undergraduate program covers four years of education, and this cohort has only attend three years of bachelor in 2015/2016. Given the definition of net dropout rate (they can either be graduated or dropout), it would increase their fraction of dropout by construction. Thus, evaluating this variable for 2012/2013 cohort is interesting due to the fact that it was the first increase in academic requirements.

year students, which is the sub-population of students with the highest probability of dropping out.

The DID model compares students who performed higher than the academic requirements of Period I but not overcame those of Period II or 2012's (Treatment Group), with students who do not meet the academic requirements of Period I (Control Group), before and after the reform:

$$\text{Dropout}_{it} = \alpha + \beta \text{Treatment}_{it} * \text{Period II}_t + \gamma \text{Treatment}_{it} + \delta \text{Period II}_t + \nu \text{X}_{it} + \epsilon_{it} \tag{22}$$

where Treatment_{it} is a dummy variable that takes value one if the students belongs to the treatment group and zero otherwise, Period II_t takes value one if the academic year is 2013 or higher, and X_{it} is a vector of student observable characteristics. Bénabou and Tirole (2000) model predicts that when the academic requirements increase, some of the weaker agents types would *give up*, exert zero effort and drop out from higher education. Results show that an the increase in the academic requirements of Period II and 2012 did not have any statistically significant impact on students drop out. Students who theoretically would not meet the academic requirements for the next academic year but they do with the *weaker* standards, do not significantly increase their level of drop out, neither these who were surprised by the reform (in 2012 and 2013 respectively) nor these of the whole Period II. This result seem to be true for first and non-first year students. The increase in the academic requirements does not seem to be high enough to induce these students to drop out from higher education. In addition, the RDD-DID analysis shows no statistically significant change in dropout from higher education across periods.

H 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 complied with a minimum fraction of credits earned 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 earned 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 earned the year before application.
- *Period II (2013–2015)*: academic standards were based on the fraction of credits earned 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: External Validity.

	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: Self-constructed Table with data from the Spanish Ministry of Education.

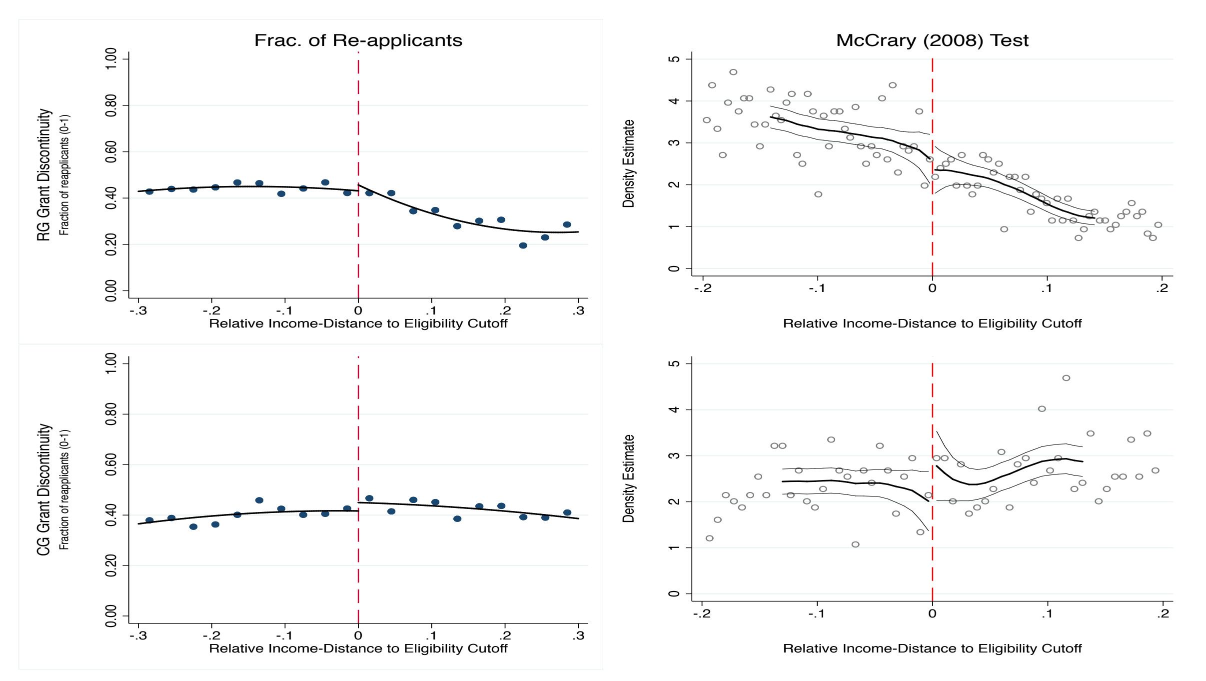
Table Appendix B1: McCrary (2008) Test for Manipulation of the Forcing Variable for Different Treatment Samples in FW and T3 grant.

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 (T3) (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 T3 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)		**T2 Discontinuity ($A+\Delta$/A)**				**T1 Discontinuity (A/0)**			
		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	.13	.60	.06	.006	-.079	.647	.10	.004
	(2010-2012)	(.22)				(.12)			
Total Applicants	Period II	.18	.79	.07	.006	-.107	.80	.10	.004
	(2013-2015)	(.23)				(.13)			
B. By Gender									
Females	Period I	-.14	.33	.05	.009	-.06	.34	.096	.006
	(2010-2012)	(.43)				(.17)			
	Period II	.29	.81	.05	.009	.004	.02	.072	.006
	(2013-2015)	(.36)				(.23)			
Males	Period I	.16	.61	.07	.009	-.11	.55	.074	.006
	(2010-2012)	(.25)				(.2)			
	Period II	.18	.49	.06	.008	-.03	.16	.10	.006
	(2013-2015)	(.36)				(.18)			
C. By PAU Percentile Rank									
Above Median	Period I	-.05	.19	.07	.008	-.14	.75	.07	.005
	(2010-2012)	(.27)				(.19)			
	Period II	.05	.17	.07	.008	-.096	.48	.08	.005
	(2013-2015)	(.28)				(.19)			
Below Median	Period I	.28	.83	.07	.01	-.016	.07	.06	.007
	(2010-2012)	(.34)				(.24)			
	Period II	.20	.47	.06	.009	-.016	.07	.08	.007
	(2013-2015)	(.43)				(.22)			
D. By residence condition									
Living with parents	Period I	.12	.45	.07	.007	.075	.52	.09	.005
	(2010-2012)	(.26)				(.14)			
	Period II	-.11	.39	.07	.007	.054	.32	.09	.005
	(2013-2015)	(.29)				(.16)			
Living outside the family home	Period I	.14	.38	.07	.012	-.65	1.76	.059	.008
	(2010-2012)	(.38)				(.37)			
	Period II	.62	1.87	.09	.01	-.46	1.56	.078	.008
	(2013-2015)	(.33)				(.29)			

Notes: The McCrary test is performed separately for each treatment sample. The T1 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 T2 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 T1 and T2 Discontinuitys by period and subgroup sample.

Treatment Sample: (Income Eligibility Thresholds)		**T2 Discontinuity** ($A + \Delta$/A)		**T1 Discontinuity** (A/0)	
Period: (academic years)		**Period I** (2010-2012) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**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 triangular 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 T1 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 T2 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 T1 and T2 grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** $(A + \Delta/A)$		**T1 Discontinuity** (A/0)	
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 triangular 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 T1 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 T2 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 T1 and T2 grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** $(A+\Delta/A)$		**T1 Discontinuity** (A/0)	
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	0.057	-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
B. Sensitivity Analysis				
B. 1 Half of the optimal bandwidth				
Non-parametric Estimates	-0.131	0.087	-0.054	0.490**
	(0.270)	(0.223)	(0.172)	(0.201)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	5.971	6.291	5.908	6.155
B. 2 Twice of the optimal bandwidth				
Non-parametric Estimates	-0.158	0.013	-0.021	0.363***
	(0.150)	(0.132)	(0.114)	(0.112)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	5.971	6.291	5.908	6.155
C. RD Robust				
Non-parametric Estimates	-0.135	0.088	-0.001	0.501**
	(0.274)	(0.225)	(0.211)	(0.201)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	5.971	6.291	5.908	6.155
D. Baseline estimates with controls				
Non-parametric Estimates	-0.065	0.013	-0.159	0.273**
	(0.154)	(0.140)	(0.104)	(0.124)
	[3,402]	[3,549]	[6,093]	[5,868]
Baseline mean	5.971	6.291	5.908	6.155
E. Placebo test with midpoint between T1 and T2				
Non-parametric Estimates	0.0026	0.1386		
	(0.120)	(0.136)		
	[3,833]	[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 triangular 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 T1 and T2 cutoffs.Baseline mean refers to the average GPA above the eligibility threshold. The T1 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 T2 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 Fraction of Credits Pased at T1 and T2 grants by period.

Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** $(A+\Delta/A)$		**T1 Discontinuity** (A/0)	
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	-0.017 (0.028) [3,402]	0.016 (0.026) [3,549]	0.006 (0.020) [6,093]	0.059*** (0.021) [5,868]
Baseline mean	0.78	0.80	0.77	0.79
B. Sensitivity Analysis				
B. 1 Half of the optimal bandwidth				
Non-parametric Estimates	-0.035 (0.041) [3,402]	0.013 (0.037) [3,549]	0.017 (0.028) [6,093]	0.059** (0.030) [5,868]
Baseline mean	0.779	0.805	0.769	0.787
B. 2 Twice of the optimal bandwidth				
Non-parametric Estimates	-0.021 (0.020) [3,400]	0.002 (0.018) [3,284]	0.003 (0.016) [6,087]	0.046*** (0.016) [5,855]
Baseline mean	0.779	0.805	0.769	0.787
C. RD Robust				
on-parametric Estimates	-0.035 (0.041) [3,402]	0.020 (0.029) [3,549]	0.017 (0.028) [6,093]	0.060** (0.030) [5,868]
Baseline mean	0.779	0.805	0.769	0.787
D. Baseline estimates with controls				
Non-parametric Estimates	-0.010 (0.024) [3,402]	0.012 (0.024) [3,549]	-0.014 (0.017) [6,093]	0.037** (0.019) [5,868]
Baseline mean	0.779	0.805	0.769	0.787
E. Placebo test with midpoint between T1 and T2				
Non-parametric Estimates	0.0021 (0.017) [3,833]	0.0150 (0.016) [5,829]		
Baseline mean	0.777	0.809		

Notes: The table shows the RDD non-parametric estimates for applicants' average GPA. Panel A shows the baseline results estimated using a triangular 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 T1 and T2 cutoffs.Baseline mean refers to the average GPA above the eligibility threshold. The T1 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 T2 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 D3: Discontinuities in Average Awarded Grant and Average GPA at Fee Waiver (FW) and Displacement and other needs grant (T3) 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) (1)	**Period II** (2013-2015) (2)	**Period I** (2010-2012) (3)	**Period II** (2013-2015) (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 (T3)

Treatment Sample: (Income Eligibility Thresholds)	**Avg. Awarded Grant (euros)** (Threshold 3)		**Avg. GPA (0-10)** (Threshold 3)	
Period: (academic years)	**Period I** (2010-2012) (5)	**Period II** (2013-2015) (6)	**Period I** (2010-2012) (7)	**Period II** (2013-2015) (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				
Non-parametric Estimates	693***	56	0.200	0.172
	(45.053)	(48.702)	(0.238)	(0.193)
	[2,896]	[2,724]	[2,895]	[2,724]
Baseline mean	98.90	394.1	5.748	6.154
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 triangular 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 T3 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 D4: Discontinuities in Average Awarded Grant, Average GPA, Fraction of Credits Earned and Dropout at Residence Grant and Compensate Grant in 2012.

Treatment Sample: (Income Eligibility Threshold)	**T2 Discontinuity** (A/0)	**T1 Discontinuity** ($A + \Delta$/A)
	(1)	(2)
A. Average Allowance Amounts (euros)		
Non-parametric Estimates	2,792***	657***
	(213.989)	(141.691)
	[1,035]	[2,038]
Baseline mean	1,461	14.20
B. Average GPA (0-10)		
Non-parametric Estimates	-0.660	-0.392
	(0.401)	(0.298)
	[1,035]	[2,037]
Baseline mean	6.28	5.98
C. Fraction of Credits Earned (0-1)		
Non-parametric Estimates	-0.078	0.017
	(0.054)	(0.029)
	[1,035]	[2,037]
Baseline mean	0.81	0.77
E. Dropout from higher education		
Non-parametric Estimates	0.013	-0.000
	(0.011)	(0.010)
	[1,035]	[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 triangular 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 D5: Discontinuities for the mechanisms variables at T1 and T2 grants by period and term.

	First Term (Fall)				Second Term (Spring)			
Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** ($A+\Delta$/A)		**T1 Discontinuity** (A/0)		**T2 Discontinuity** ($A+\Delta$/A)		**T1 Discontinuity** (A/0)	
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 triangular 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: RDD-DID Estimates for T1 Grant.

Dependent Variable	Basline Mean	RDD-DID Estimate
A. Average Allowance Amounts (euros)		
	25.89	121.9168
		(85.365)
B. Average GPA (0-10)		
	5.908	0.3162**
		(0.148)
C. Fraction of Credits Earned (0-1)		
	0.769	0.0505**
		(0.023)
D. Official Dropout (0-1)		
	0.03	-0.0190
		(0.018)
E. Degree Completion (0-1)		
	0.91	0.0964*
		(0.056)
N		11,965

Notes: Robust standard errors are clustered at the student level and displayed in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table F1: Difference in Baseline Means by period and treatment sample.

Treatment Sample: (Income Eligibility Thresholds)	**T2 Discontinuity** ($A + \Delta$/A)			**T1 Discontinuity** (A/0)		
	Baseline Mean PI (1)	Difference PI vs. PII (2)	P-Value	Baseline Mean PI (3)	Difference PI vs. PII (4)	P-Value
Female	.49	.017	.56	.47	.025	.44
Spanish	.95	.014	.02	.99	-.0023	.28
Access to University Percentile rank	54.57	2.27	.00	56.54	.38	.25
STEM degree	.34	-.02	.21	.40	-.025	.36
Households taxable income (euros)	17,959	1,336	.00	43,703	3,306	.00
Number of family members	3.7	.0074	.46	3.7	.042	.28
Disability	.011	-.007	.13	.014	.005	.66
Large family condition	.12	-.016	.08	.13	.012	.84
Live outside the family home	.29	-.027	.14	.3	.005	.00
Entrepreneur Parent	.07	-.005	.00	.04	.003	.29
Blue Collar Parent	.42	-.05	.00	.2	-.034	0.01
Self-Employed Parent	.064	.004	.4	.023	.0044	.16
Awarded Grants	1	-.013	.44	.41	.088	.36

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 T1 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 T2 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 G1: Logistic models of net dropout rate: Academic year 2011-12 vs. 2012-13.

Variables	**First Year Students**			**Non-first Year Students**		
	(1)	(2)	(3)	(4)	(5)	(6)
Academic year 2012–2013	0.235	0.235	0.232	-0.195*	-0.168	-0.143
	(0.155)	(0.157)	(0.158)	(0.114)	(0.116)	(0.117)
Households taxable income (euros)		-0.000	-0.000		-0.000***	-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
Female		-0.659***	-0.698***		-0.194	-0.184
		(0.176)	(0.177)		(0.131)	(0.132)
Access to University Percentile rank		-0.008***	-0.008***		-0.007***	-0.007***
		(0.003)	(0.003)		(0.002)	(0.002)
STEM degree		-0.328*	-0.284		1.011***	1.038***
		(0.178)	(0.180)		(0.127)	(0.130)
Spanish		0.625	0.611		0.987**	0.939**
		(0.412)	(0.415)		(0.459)	(0.461)
Number of family members			-0.255***			0.219***
			(0.098)			(0.071)
Live outside the family home			0.318*			0.215
			(0.171)			(0.137)
Disability			0.043			0.669*
			(0.586)			(0.375)
Large family condition			0.163			-0.512**
			(0.274)			(0.225)
Entrepreneur Parent			0.101			-0.145
			(0.314)			(0.240)
Blue Collar Parent			-0.131			-0.301**
			(0.189)			(0.135)
Self-Employed Parent			0.102			-0.597*
			(0.338)			(0.319)
Observations	1,361	1,361	1,361	6,390	6,390	6,390

Notes: 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 G2: Logistic models of yearly dropout rate (2010–2015).

Variables	**First Year Students**			**Non-first Year Students**		
	(1)	(2)	(3)	(4)	(5)	(6)
Period II (2013–2015)	-0.226	-0.226	-0.207	-0.731***	-0.715***	-0.704***
	(0.151)	(0.152)	(0.152)	(0.157)	(0.157)	(0.158)
Households taxable income (euros)		0.000*	0.000**		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Female		-0.369**	-0.386**		-0.087	-0.088
		(0.169)	(0.170)		(0.161)	(0.161)
Access to University Percentile rank		-0.019***	-0.019***		-0.013***	-0.015***
		(0.003)	(0.003)		(0.003)	(0.003)
STEM degree		-0.024	0.005		0.372**	0.421***
		(0.164)	(0.166)		(0.159)	(0.161)
Spanish		0.062	0.042		0.098	0.012
		(0.350)	(0.352)		(0.391)	(0.393)
Number of family members			-0.233***			-0.049
			(0.090)			(0.089)
Live outside the family home			0.111			0.357**
			(0.172)			(0.166)
Disability			-1.346			-0.322
			(1.020)			(0.599)
Large family condition			-0.124			0.347
			(0.288)			(0.241)
Entrepreneur Parent			-0.078			-0.143
			(0.300)			(0.295)
Blue Collar Parent			-0.370**			-0.542***
			(0.182)			(0.185)
Self-Employed Parent			-0.329			-0.207
			(0.372)			(0.349)
Observations	8,440	8,440	8,440	21,106	21,106	21,106

Notes: 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 G3: DID model of yearly dropout rate (2010–2015).

A. Period I vs. Period II						
Variables	**First Year Students**		**First Year Students (2010–2013)**		**Non-first Year Students**	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment*Period II	0.011	0.012	0.016	0.017	-0.001	-0.001
	(0.009)	(0.009)	(0.013)	(0.013)	(0.004)	(0.004)
Treatment	-0.043***	-0.042***	-0.043***	-0.042***	-0.018***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Period II	-0.020**	-0.021***	-0.022*	-0.024**	-0.002	-0.005
	(0.008)	(0.008)	(0.012)	(0.012)	(0.004)	(0.004)
Student Controls	No	Yes	No	Yes	No	Yes
Observations	10,424	10,424	8,999	8,999	15,921	15,921

B. Period I vs. Increase in 2012's Requirements						
Variables	**First Year Students**		**First Year Students (2010–2012)**		**Non-first Year Students**	
	(7)	(8)	(9)	(10)	(11)	(12)
Treatment*Year2012	0.004	0.005	0.006	0.007	-0.005	-0.006
	(0.008)	(0.008)	(0.010)	(0.010)	(0.004)	(0.004)
Treatment	-0.034***	-0.030***	-0.034***	-0.030***	-0.015***	-0.017***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)
Year 2012	-0.029***	-0.036***	-0.035***	-0.045***	0.001	-0.002
	(0.006)	(0.007)	(0.008)	(0.010)	(0.003)	(0.004)
Observations	8,992	8,992	7,171	7,171	12,617	12,617
Student Controls	No	Yes	No	Yes	No	Yes

Notes: Treatment refers to the group of students whose performance is in between academic requirements of Period II (2012) and Period I. These students would meet the requirements in Period I, but not in Period II (2012). Student controls include all the student predetermined observable characteristics of the students available in the data. Robust standard errors are clustered at the student level and displayed in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H1: 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:

Variable component formula.

$$C_j = C_{min} + \left[(C_{total} - S * C_{min}) * \frac{(N_j/N_{max} * (1 - (\frac{R_j}{R_{max}}))}{\sum_{i=1}^{S}(N_i/N_{max}) * (1 - (\frac{R_i}{R_{max}})} \right] \tag{23}$$

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.